Master Thesis

Identify Feature Fatigue in Smartphone Markets via Feature Importance of Random Forests

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Abstract

Feature fatigue refers to the phenomenon whereby when consumers assess a product, adding the number of features or excessively enhancing the same feature are positively associated with the perception of the product's capabilities before purchase but negatively associated with its perceived usability after purchase, causing dissatisfaction and reduction of consumer equity in the long term. This paper aims at analyzing which smartphone features may cause feature fatigue in six major continental markets using comprehensive sales data collected by IDC. A random forest model is established to generate feature importance scores which are in turn used to identify the features causing fatigue. The results suggest that consumers in high-income regions as Western Europe and USA exhibit feature fatigue more rapidly and intensively. The clear distinction between Western Europe, USA and the other four markets may be attributed to differences in income level, culture and demographics. The limitation of the study is that the distributions of the importance scores are unknown. To generate these distributions would require substantially more computing power, which could be explored in future studies.

Key words: feature fatigue, feature importance, random forest, smartphone

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1 Introduction

Nearly three decades have passed since IBM unveiled the first smartphone in 1992 (Reid, 2018). Today, the number of smartphone users worldwide stands at 3.5 billion (Statista [1], 2020). Smartphones have become an indispensable component in most consumers' lives. The expansion of the smartphone market size did not show any signs of slowing down for decades until the first jitter in the industry was felt in 2019 when sales worldwide registered a 2.3 % decline, as reported by the International Data Corporation[2] (IDC). Forecasts made by *the IDC Worldwide Quarterly Mobile Phone Tracker*[3] would see a further year-on-year drop of 9.5 % in worldwide shipments in 2020, resulting in 1.2 billion units. An increasingly saturated market exacerbates competition among smartphone manufacturers, with many leading market players - such as Samsung, Huawei and Apple – responding by introducing more and better features with every new phone generation, i.e., ever faster processors, sharper screens and more powerful cameras in this relentless grab for a slice of market share. This paper questions whether such "feature competition" is the optimal response of smartphone players to consumer dynamics, or, whether it may be a myopic response to competitive dynamics. The goal is to answer this question through a data sciences approach that can help smartphone manufacturers understand and quantify the impact of different features on consumers' utility and choices. A random forest model is created to generate the feature importance with 18 smartphone features modelled as the independent variables and sales of individual phone models (per year, per region) as the dependent variable.

The crux of the idea is as follows. On the one hand, obviously better and more features increase the utility that a consumer can derive from a given product (in this case a smartphone), and thus, smartphones with more powerful features will satisfy important customer needs. On the other hand, the industry's tendency to continuously upgrade smartphone features may lead consumers to increasingly perceive certain smartphone features (or performance levels) as superfluous, i.e., as exceeding their utilitarian needs. Incorporating such unnecessary features into a product may thus render the offering too complex, causing dissatisfaction of the consumers due to a phenomenon called in the marketing literature as the *"feature fatigue"* (Thompson et al., 2005). While the downturn in the global smartphone market may give some "model free evidence" that *feature fatigue* is already being felt by consumers, no existing study has properly documented the effect and quantified its impact, as I do in this thesis.

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[1] https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/
[2] https://www.idc.com/getdoc.jsp?containerId=US46194820
[3] https://www.idc.com/getdoc.jsp?containerId=prUS46802520

An in-depth look into industry trends further suggests that "*feature fatigue*" may already be hurting smartphone sales. For example, major market players such as Samsung have started to "drill down" on features not valued sufficiently by customers, such as when it chose to abandon the extravagant yet idle feature of the curved screen on its latest Galaxy S20 series. A time has come for smartphone manufactures to focus on the enhancements of a limited number of most important features that take into account not only the capabilities of products perceived by consumers before purchase but also the actual experienced usability after purchase, minimizing *feature fatigue*. Yet, this requires robust models capable of quantifying the impact of different product features on consumer utility, and how such impact changes over time.

More specifically, this paper proposes a new modeling approach capable of distinguishing critical vs. superfluous smartphone features, i.e., those with a significant (vs. insignificant) impact on smartphone sales using a comprehensive data set provided by IDC regarding global smartphone sales of all smartphone models in six geographical regions over a period of 16 years (between 2004 and 2019). The proposed methodology relies on the application of feature importance in machine learning to distinguish critical from superfluous features.

This study contributes to the literature in three main ways. First, prior studies regarding smartphone features do not offer a scalable model that firms can calibrate using secondary data. Instead, prior literature focuses mainly on detecting the correlations between certain phone features and user satisfaction scores gathered via questionnaires designed for hypothetical scenarios and experiments, such as in choice-based conjoint analysis which quantifies consumers *part-worth* for different product feature levels (Green et al., 2001). The findings of such studies may paint an inaccurate picture of the reality due to the limitations in their methodologies and data, often as a result of the shortcomings of questionnaires as a data collection methodology[4]. Relatedly, prior literature does not offer a complete view of what the key drivers of smartphone sales are. The *IDC Worldwide Smartphone Tracker Data* obtained for this study offers a unique opportunity to document these drivers. Specifically, it enables the calibration of a feature-based model on real-world secondary data, allowing a rigorous derivation of which smartphone features are the most impactful on smartphone sales[5].

[4] For instance, Couper (2000) summarized 4 types of common errors of questionnaires that led to bias: sampling error, coverage error, nonresponse error, and measurement error – deviation of answers from respondents' true opinions.

[5] Note that across various industries, there has been abundant empirical research into what factors influence sales. Coad (2009) summarized a number of determinants of sales from empirical evidence, among which are firm size, firm age, innovation, financial performance, relative productivity, industry specific factors such as competition and concentration, and macroeconomic factors such as GDP growth, inflation and fiscal policies. For this paper, the aim is not to include all these potential drivers of smartphone sales to achieve high prediction accuracy.

Second, most prior models ignore temporal dynamics even though it is clear that what drives a product's sales one year may be different from what drives that product's sales five years down the road. In this paper, I leverage the obtained long panel data to quantify how the importance of various smartphone features on smartphone sales *changes over time*. More precisely, by exploring the time dimension I will establish a model that offers a dynamic view over a period of 16 years. My proposed model reveals how important smartphone features evolved over time. In turn, such quantified dynamics allow us to answer the question of whether or not the smartphone industry is already facing a ceiling due to *feature fatigue* and also to identify specifically which features may have been causing *feature fatigue* and to what extent. The findings would also enable market players to not only check the validity of past decisions by verifying with real-life developments, but also heralding which adaptations to implement in the near future to remain competitive.

Third, most prior empirical studies also ignore spatial heterogeneity, even though what drives a product's sales in region A may of course be different from region B. In this paper, I also account for cross-regional heterogeneity by revealing the differences of feature importance in different regions across the globe. This allows me to offer more precise recommendations to smartphone companies and also to better quantify in which regions is *feature fatigue* more or less of an issue.

In an ideal world, true consumer preferences may be revealed by analyzing their brains. Nobel Laureate Francis Crick (2003) first established the framework of the general nature of the neural activities in the brain related to different aspects of consciousness: for instance, the perceptions of various colors, shapes or movements. The development of neuromarketing has enabled scientists and marketers to measure and quantify consumers' preferences by scanning their brains when they are interacting with different product features in a laboratory. Kühn et al. (2016) used functional magnetic resonance imaging (fMRI) scan results to predict chocolate sales and achieved a higher prediction accuracy compared to using self-stated preference as a predictor. Before the development in neuroscience allows such experiments to be conducted on a large-scale and at much lower costs, using sales data of numerous smartphone models with various features is certainly a better alternative than small-scale questionnaires. The former generates a more realistic insight of what drives consumer preferences.

This paper neither seeks to prove causalities between smartphone features and sales, nor to achieve the highest possible prediction accuracy of smartphone sales. In terms of methodology, this paper attempts to uncover whether the aforementioned *feature fatigue* has occurred in these smartphone markets – and how it has changed over time and across regions - I employ feature importance and feature selection methods from the machine learning toolbox. In short, global smartphone sales data provided by IDC is used to establish a Random Forests (RF) model to answer the question: what smartphone hardware and software features were, among all features, the ones that caused feature fatigue – i.e., most negatively associated with smartphone sales - from 2004 to 2019 on a global scale and in the following regions: Western Europe, Central & Eastern Europe, Asia / Pacific (excluding Japan and the People's Republic of China), USA, Latin America, Middle East & Africa. The number of unique smartphone models worldwide in the data set recorded a dramatic increase from 802 in 2004 to 7594 in 2019. History of smartphone developments in the same regions and over the same time period are used to verify the findings. The reasoning of the selection of the RF model is explained in the third section of this paper.

2 Feature Fatigue and Its Implications in the Smartphone Industry

The intuitive belief that more features are better for a product is at first glance hard to reject. Brown and Carpenter (2000) experimentally proved that even adding trial features to a product could provide purchase incentives for consumers over its competitors. In 2017 Samsung launched the TV series “the Frame” that could function as a decorative artistic painting – an indication of how excruciatingly fierce the competition in the electronics industry had become. We live in an era of consumerism when people’s daily lives are constantly bombarded by dazzling market offerings whose ultimate utilitarian values are questionable. Thompson et al. (2005) challenged the notion of “more is better” by introducing the concept of “*feature fatigue*”. The study quantified consumers’ evaluations of a product into a two-dimensional “capability versus usability” perspective. The study found that when consumers assessed a product, adding the number of features in a product was positively associated with the perception of the product’s capabilities but negatively associated with its perceived usability and that consumers gave more considerations to the capabilities of a product before purchase than after purchase.

Wu and Wang (2011) established a six-dimensional perceived value model to assess the effect of adding features on customer's perceived value of the product before and after use. Wu et al. (2014) also applied text-mining techniques to extract information from the reviews of customers in order to study the usability of products after purchase. Li and Wang (2011) constructed a Bayesian networks model based on data collected via questionnaires to identify the features that most likely led to *feature fatigue*. According to Thompson (2005), by taking advantage of consumers’ preference for capability before purchase, loading an excessive number of features onto a product may increase short-term sales, but the impaired usability in the future would negatively affect long-term customer equity. To find the suitable balance is vital to a product's continuing success. Rust et al. (2006) suggested that maximizing a product's net present value of lifetime customer profit stream by calculating its optimal number of features that balances between capability and usability is the solution to defeat *feature fatigue*.

As a relatively more sophisticated electronic product, smartphones have a rather large number of features, granting them an innate potential for *feature fatigue*. Keijzers et al. (2008) found that in the UK smartphone market, 63% of the product returns were completely unrelated to hardware or software malfunctions. These complaints were mainly regarding usability issues such as difficulty in device configurations.

The original concept of *feature fatigue* was defined as when products being equipped with too many features lead to consumers' dissatisfaction after use because of their high levels of complexity. The "capability" benefits before purchase are positively associated by consumers with the number of features a product has, as opposed to the "usability" costs in the long-term after purchase (Thompson et al., 2005). According to this definition, the magnitude of "capability" of a product is increased by the number of features. As an extension to this definition, not only too many features, but also overly enhanced features may cause *feature fatigue*. For instance, the upgrade of the feature from QHD to 4K screen resolutions introduced to many flagship smartphone models is imperceptible with human eyes. Therefore, it is only logical to expand the definition of *feature fatigue* to include the effect also caused by excessive and superfluous features – enhancements of features that do not generate incremental utilitarian value to consumers. Thompson et al. (2005) highlighted that consumers' expertise would reduce the perception of *feature fatigue* and increase the long-term usability of a product. As different demographics bear different levels of expertise in using smartphones, consequently I examine the variation in the effects of *feature fatigue* across different geographical regions from 2004 to 2019. To achieve this, interpretation of the Blackbox Random Forests model would be required. Partial Dependence Plot (PDP) is applied to label the features that have diminishing positive impact on sales as the culprits of *feature fatigue* in the respective regions.

3 Quantifying Consumers' Assessments of Product Features: A Data Science Perspective

Smartphones nowadays are equipped with a long list of features whose analyses inevitably require techniques that can deal with high dimensionality. High-dimensional data is frequently encountered by researchers. Confronted by the challenge of identifying relevant features, the topic of feature selection has drawn considerable attention across many scientific domains, with supervised learning receiving significantly more treatments than unsupervised learning and classification problems making more appearances in academia than regression ones (Guyon & Elisseeff, 2003). In order to answer the research question of this study, feature importance ranking and feature selection are applied.

There are several merits of feature selection: enabling a better understanding and diagnoses of the underlying data generation process via ranking the importance of features; reducing the dimensionality of data for improved model prediction accuracy; reducing storage and computational resources required for performing analyses (Guyon & Elisseeff, 2003). The feature importance scores generated during the feature selection process enables the quantifying of each smartphone feature's impact on sales. The three categories of feature selection, namely wrapper methods, filter methods and embedded methods and their comparisons are described as follows.

3.1 Applications of Feature Selection Methods

Feature selection is becoming particularly imperative as big data has encroached into nearly all scientific disciplines, especially in the domains of text processing and gene expression array analysis (Guyon & Elisseeff, 2003). Diaz-Uriarte Ramon and Alvarez de Andres (2006) applied random forests to select a small set of crucial genes for diagnostic purposes in the medical industry. Iannario et al. (2012) demonstrated using random forests to extract important features for customer satisfaction towards Italian espresso coffee. Fontana et al. (2013) used random forests to capture the most important variables for food intake detection. Hoyle et al. (2015) applied Adaptive Boosting to find features that have the most predictive power in photometric redshift estimation. Zhao et al. (2019) used several machine learning techniques to evaluate what features influenced the likelihood of consumers to choose a certain category of Uber service.

3.2 Feature Selection Methods

Wrapper Methods

Kohavi and John (1997) brought wrapper methods into the spotlight while summarizing the numerous definitions of feature relevance. Wrapper methods attempt to search for a subset of optimal features among all features that are evaluated according to a performance measure, for instance prediction accuracy. Since wrapper methods generate the performance scores only after model training and cross validation, unsurprisingly Kohavi and John (1997) highlighted that overfitting and run time are the weaknesses.

Filter Methods

Lazar et al. (2012) demonstrated popular filter methods holistically and elaborately. Unlike wrapper methods, the assignment of feature ranking is executed before the model training process. Filter methods primarily rely on calculating a relevance score for each feature based on a chosen scoring function. The assessments of the features are carried out independently of the model, extracting only the intrinsic properties of the features. As a result, a ranking of features is generated based on the scores. There is a crucial disadvantage of filter methods: The effects of the assessed features on the performance of the model are not taken into consideration. More precisely, certain irrelevant features that can potentially improve performances may be ignored while not being able to eliminate correlated features that may negatively affect the performance of the model (Kohavi and John,1997).

Embedded Methods

Embedded methods, as its name suggests, embed the task of feature assessment in the model training process. Typical embedded methods include random forests, decision trees, regression trees and Lasso regression. Lasso regression eliminates unimportant features in the training process (Tibshirani, 1996) while random forests, decision trees and regression trees generate feature importance rankings via variable permutations (Breimen, 2001).

Overviews

There are a number of papers that produced overviews of the above-mentioned feature selection and feature ranking methods. Guyon and Elisseeff (2003) evaluated different methods with regards to multivariate feature selection, feature ranking, feature validity assessment methods and efficient search methods. Saeys et al. (2007) illustrated the benefits and the necessity of the most essential feature selection methods and shed light on several adapted procedures developed for applications in different scientific fields. Li et al. (2017) presented a structured overview of recent advances in feature selection, revisiting the topic of feature selection from a data perspective by reviewing popular feature selection methods for diverse types of data. Venkatesh and Anuradha (2019) described in detail how major feature selection methods were effective in dealing with the ongoing challenge of rapidly increasing size of data.

Models Individually Studied

Martilla and James (1977) recorded a common practice at the time in corporations of how the feature importance ranking was obtained for marketing purposes via questionnaires. In an era when regression models were the primary tool for academic research, Green et al. (1978) compared three prevalent criteria used to measure relative contributions of predictor variables in linear regression and introduced a novel 6-step approach to calculate variable importance. Budescu (1993) described the conventional definitions of variable importance ranking in the case of multiple regression and proposed a new approach named dominance analysis in order to deal with the weaknesses of the former. Grömping (2007) highlighted the common problem of correlated predictor variables in the application of linear regression, thus proposing to assess the relative importance of the variables via variance decomposition.

Ishwaran (2007) compared the characteristics of variable importance ranking in regression trees and random forests. Genuer et al. (2010) provided experimental insights into the behavior of the variable importance ranking generated by random forests for the purpose of interpreting relevant variables. Archer and Kimes (2008) tested the effectiveness of random forests in identifying truly discriminative predictors in the presence of different levels of correlation and concluded that random forests is an excellent choice. Gregorutti et al. (2017) demonstrated the use of recursive feature elimination in the context of random forests.

3.3 Comparisons of Feature Selection Methods

Many scholars have evaluated and compared feature selection methods in terms of different performance metrics. To name a few: prediction accuracy, interpretability, stability and computational costs such as run time and memory usage. Díaz-Uriarte (2006) compared random forests with a number of feature selection methods and found that random forests was the most attractive technique in preserving a small set of features while maintaining an outstanding prediction performance. Saeys et al. (2007) evaluated the three major categories of feature selection methods in the application of a variety of domains and summarized their respective strengths and shortcomings. Later, Saeys et al. (2008) addressed the issue of robustness in feature selection methods – the discrepancies of selected features as a result of small changes to data sets. He evaluated filter methods and embedded methods from this perspective and found that ensemble methods achieved a better trade-off between robustness and accuracy. Grömping (2009) compared the mechanism of how linear regression and random forests generated the feature importance ranking, providing a thorough understanding of the concept of feature importance in these two techniques. Fernández -Delgado (2014) assessed 179 algorithms on 121 data sets based on one single metric – prediction accuracy and concluded that random forests achieved the best performance. **Table 1.1** displays an overview of the comparisons of the three major feature selection methods.

Method Type	*Advantages*	*Disadvantages*	*Feature Selection*	*Feature Ranking*
Filter	Independent of algorithm (stability) Computationally inexpensive	Independent of algorithm (accuracy)	Before training	Able to generate
Wrapper	Exhaustive sub-group search enhances performance Less prone to local optima	High risk of over-fitting High computational costs Algorithm dependent selection (stability)	After training	Unable to generate
Embedded	Affordable computational costs Importance ranking considers effects on response variable	Algorithm dependent selection (stability)	During training	Able to generate

Table 1.1: comparisons of the three major feature selection methods

3.4 Select the Feature Selection Method for This Study

In order to evaluate each smartphone feature's relationship with sales, it is important to identify and select feature selection methods that generate robust feature importance rankings. Wrapper methods are excluded because their feature selection process involves greedy stepwise selections and exhaustive sub-group searches that do not permit the derivation of a feature importance ranking (Kohavi and John, 1997). Despite being able to quantify the importance of features via the calculation of relevance scores, filter methods are independent of the model. The effects of evaluated features on the performance of the model are utterly ignored (Lazar et al., 2012), giving filter methods a conspicuous disadvantage to embedded methods. There are two techniques under the embedded method category that are able to generate feature importance rankings: Linear models and Random Forests (RF). Elastic net regression, Ridge regression and Lasso regression are all liner models whose only difference lies in the regularization term. Lasso regression shrinks the coefficients of certain features to zero, leaving a set of "good" features. Interpretation of the importance of features is directly referred to the value of the coefficients of the non-eliminated features (Tibshirani, 1996). Nevertheless, Lasso regression requires the underlying assumption that the functional form between the independent variables and the dependent variable is linear - an extremely unlikely scenario for this case. Even though it is possible to add polynomials and interaction terms into Lasso to boost its capability to handle non-linearity, the computational costs would rise drastically. Henceforth, Random Forests (RF), a non-parametric method that requires no underlying assumptions and can efficiently handle large data sets and deal with complex interactions, is unequivocally a suitable choice for this analysis. In an RF model, feature importance is measured by randomly permuting the features in the out-of-bag samples and calculating the increase in the misclassification rate or mean squared error (MSE) as compared to the out-of-bag error rate or MSE with all variables intact (Breiman, 2001). The process of generating feature importance ranking in RF is discussed extensively in section 5.

4 Data

4.1 Data: Sales and Phone Features Data from IDC

The dataset used for this paper is the *IDC Worldwide Smartphone Tracker Data* obtained from International Data Corporation (IDC). The data set was provided in the form of 2 separate .xlsx files with a total size of 292 MB. The long panel data contains quarterly information regarding sales and smartphone features of all mobile phone models sold between 2004 and 2019 in the following geographical regions: Western Europe, Central & Eastern Europe, Asia / Pacific (excluding Japan and the People's Republic of China), USA, Latin America, Middle East & Africa. Each observation (row) is a smartphone model with its corresponding quarterly sales, unit price, hardware features and software features (columns).

4.2 Data Pre-processing

The process of data pre-processing is described in the following steps:

1. The two .xlsx files were converted into .csv format and merged.
2. Remove rows where *Average Selling Price (ASP)* is zero *and Sales - Units* is not zero.
3. The feature (column) *Screen Resolution* was originally recorded in the format of e.g., 1024 × 768, the number of different screen resolution types exceeds the limit of 53 levels set by *R* as a categorical variable. Therefore, the total numbers of pixels were calculated (the product of the two numbers) to convert this categorical variable into a numerical variable.
4. Observations that were not smartphones were removed.
5. Convert categorical variables into factors.

6. Remove features (columns) that cannot be processed due to restrictions of the software package: *Brand*, *Company* (*R* by default sets a limit on the maximum number of levels in a categorical variable to 53).
7. Remove features (columns) that are duplicate: *OS Variant*, *OS Version* (*OS* is retained); *Value (USD)* (The dependent variable used for the analyses is sales in units instead of sales in monetary value.)
8. Remove features (columns) that are empty: *Megapixels Band, Primary Camera, Processor Speed Band, Screen Size Band.*
9. Remove features (columns) that consumers generally do not evaluate when buying smartphones: *Air Interface, Generation, Model Name, Input Method, Processor Vendor, Processor Brand, Near Field Communication (NFC)* and *Form Factor* (after 2008 the vast majority of smartphones are full touch screen phones).

4.3 Data Descriptive Statistics

The dependent variable and 18 independent variables and their descriptive statistics used for this paper are summarized in **Table 4.1**.

The developments of the following main smartphone features between 2004 and 2019 were visualized in **Figure 4.1** by taking the average of each feature of all the smartphone models in the global market in that given year and plotting the average against the time period between 2004 and 2019: *Storage (GB)*, *RAM (GB)*, *Camera Megapixels*, *Screen Size*, *Processor Speed (GHz)* and *ASP (USD)*.

As displayed in **Figure 4.1**, during these 16 years there had been unsurprisingly consistent improvements of smartphone's main hardware features. The average storage capacity went up from around 2 GB in 2004 to over 60 GB in 2019; the average memory (RAM) increased from nearly zero in 2004 to over 3 GB in 2019; The average camera resolution improved from about 0.5 megapixels in 2004 to almost 20 megapixels in 2019; The average screen size expanded from approximately 1 inch in 2004 to 5.5 inches in 2019; The average processor speed rose from 0.1 GHz in 2004 to 2.3 GHz in 2019. The only feature that went through a downward trend was the average selling price. As the global smartphone market expanded to cover increasingly more developing economies such as African countries, along with the entry of many low-end Chinese manufactures, the average selling price of a smartphone was driven down significantly.

Independent Variables - Categorical				
Bluetooth	Yes	No		
Displaytype	LCD	OLED	N/A	
GPS	Yes	No	N/A	
Wireless Charging	Qi	Qi / PMA	None	
Multi Front Camera	Single	Dual	Tripple	None
Multi Rear Camera	Single	Dual	Tripple	Quad
	Quint	Six	None	
Processor Cores	Single Core	Dual Core	Quad Core	Octa Core
	Hexa Core	Deca Core	N/A	
Dual-SIM	Dual Standby	Dual Standby with eSIM	Single Standby	Single Standby with eSIM
	Tripple Standby +	No	N/A	
Water Proofing	IP52	IP53	IP54	IP55
	IP56	IP57	IP58	IP65
	IP67	IP68	IPX4	IPX7
	Resistance	N/A		
Biometric Authentication	3D Face Recognition	3D Face & Fingerprint - Rear	3D Face & Fingerprint - UD	Fingerprint - Front
	Fingerprint - Rear	Fingerprint - Side	Fingerprint - TBC	Fingerprint - UDP
	None			
Operating System (OS)	Android	BlackBerry OS	Linux	IOS
	Maemo/MeeGo	Palm OS	Sailfish OS	Symbian
	Tizen	webOS	Windows CE	Windows Mobile
	Windows Phone	FireFox OS	Others	

Independent Variables - Numerical	Min	Mean	Max	SD
Camera Megapixel	0	9.70	108.00	6.61
Processor Speed - Ghz	0	1.42	3.00	0.60
RAM - GB	0	1.78	12.00	1.61
Screen Size	0	4.72	7.20	1.06
Screen Resolution (in pixels)	0	1127774.00	8294400.00	1090793.00
Storage - GB	0.001	28.64	1024.00	52.82
Average Selling Price (ASP) - USD	0	296.20	8624.10	262.10

Dependent Variable	Min	Mean	Max	SD
Sales - Units	0	17474	7405172	87293

Table 4.1: Overview of variables and descriptive statistics

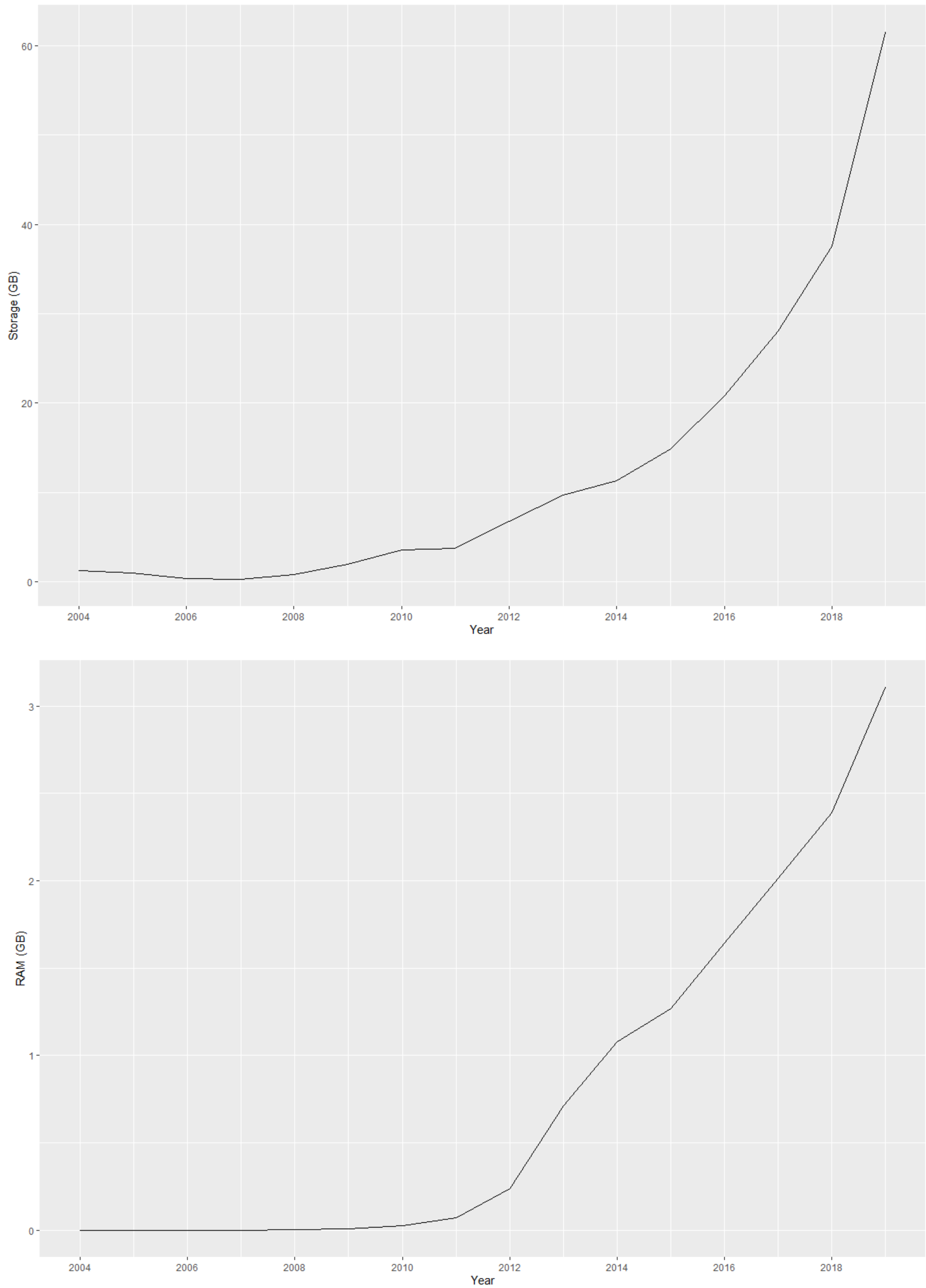


Figure 4.1: Developments of smartphone features between 2004 and 2019

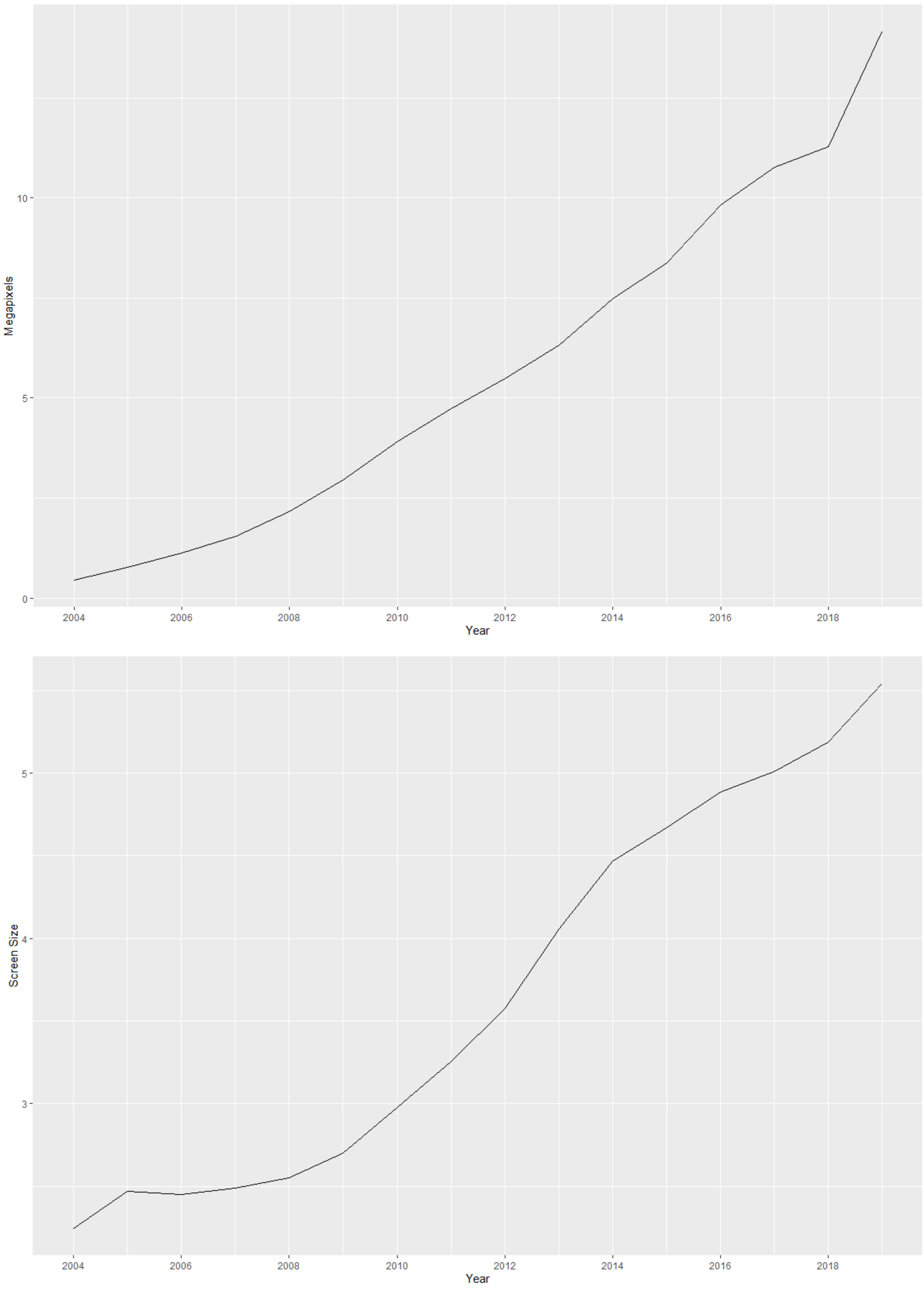
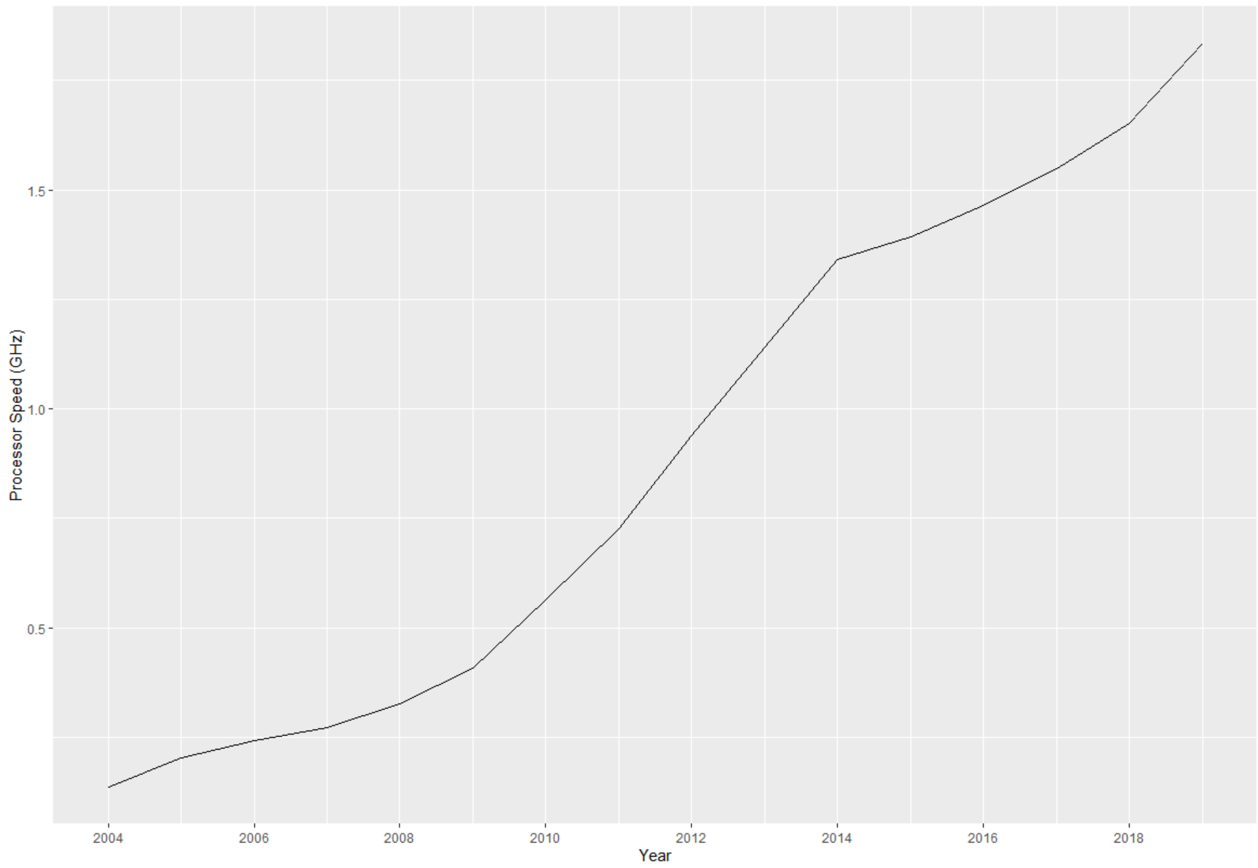


Figure 4.1(cont.): Developments of smartphone features between 2004 and 2019



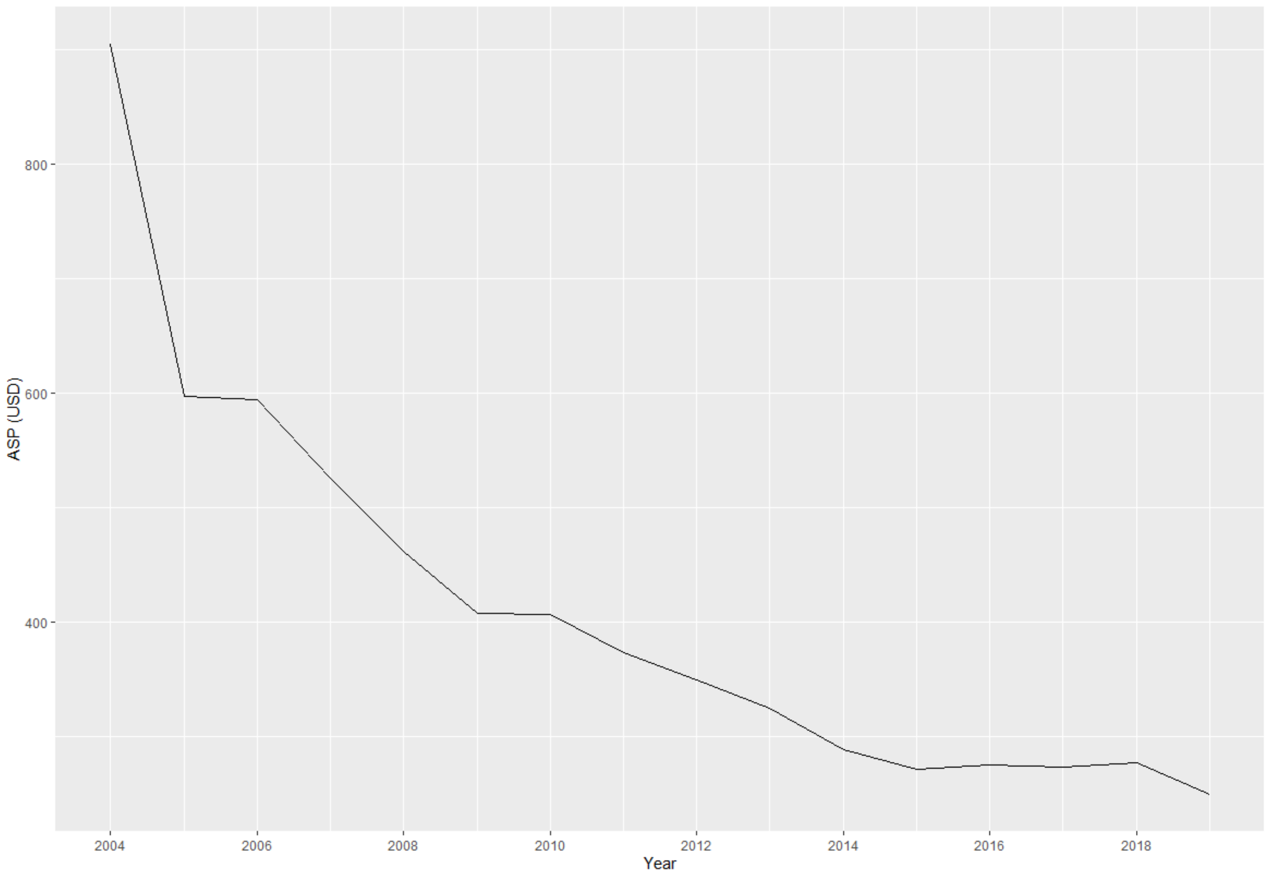


Figure 4.1(cont.): Developments of smartphone features between 2004 and 2019

5 Method

In the previous sections, I have outlined the research question and the problem I will investigate: What smartphone features may have triggered *feature fatigue* from 2004 to 2019 in different regions.

As discussed above, the goal of this paper is neither to seek high prediction accuracy or to prove causality. Rather, the problem can be treated as a proxy of "prediction problem" where I use the feature importance scores and its interpretation as a tool to reveal the elaborate relationships between smartphone features and sales and identify which features were most negatively associated with sales, i.e., causing *feature fatigue*. More precisely, the essence of this study can be broken down into two modules. First, I evaluate consumers' assessments of various smartphone features. To do so, I create a random forest model to quantify the predictive power on smartphone sales of each smartphone feature via the embedded generation of feature importance scores in the RF algorithm. Smartphone features with high predictive power can have either a substantial positive or negative effect on smartphone sales. Henceforth, I inspect the developments of the magnitude and "direction" of the "marginal returns" of these smartphone features on sales via Partial Dependence Plots (PDP). Additionally, the dynamic element of the study is to map out the variations of features' predictive power and their relationships with sales over time and then separately analyze them in different regions.

The overviews and comparison of the three feature selection methods, namely filter methods, wrapper methods and embedded methods were laid out in section 3. I also presented the reasoning of why Random Forests – an embedded method - was selected for the analyses. In the random forest model, I treat the outcome variable (sales) as my dependent variable and the 18 smartphone features as the independent variables. In this case, the "*feature fatigue* detection" can be treated as a combination of first observing the "elbows" in feature importance scores. The conspicuous "change" is crucial to the identification of *feature fatigue* because according to its definition, the variation should resemble an initially positive and then diminishing or negative trend and relationship in both the importance scores and PDPs. Otherwise, a sustained negative relationship would only indicate it has been an unwelcomed feature since the introduction instead of causing *feature fatigue*.

This section provides an overview of the methods that will be deployed as an analysis on the *feature fatigue* problem, their suitability, assumptions and (dis-) advantages.

5.1 Random Forests

Recursive partitioning methods have become widely used methods for non-parametric regression and classification in increasingly more scientific domains. Random Forests (RF) is a particularly popular method that can handle large numbers of independent variables even in the presence of complex interaction (Strobl et al., 2009). For this paper, the high-dimensionality in the data set implies non-linearity between the independent variables and the dependent variable, making RF an ideal choice for modelling thanks to its ability to approximate non-linear decision boundaries. RF is an ensemble of regression trees or decision trees that are built based on the greedy recursive binary splitting approach. These aggregated trees are then used to make predictions.

Definition

In my particular application, a random vector $\boldsymbol{v_k}$ is generated for the *k*th tree, which is constructed by bootstrapping the same number of observations (information regarding smartphone models) from the pre-processed *IDC Worldwide Smartphone Tracker Data* with replacement. The *k*th tree is independent of the previously generated vectors $\boldsymbol{v_1}, \ldots, \boldsymbol{v_{k-1}}$. Individual trees are grown using $\boldsymbol{v_k}$ and the training set. Let $\mathbf{x}$ be an input vector which contains features of a certain smartphone model. According to Breiman (2001), the collection of the individual trees forms a random forest predictor $h\ (\mathbf{x}, \boldsymbol{v_k})$ that predicts the sales of a certain smartphone model. Consequently, a random forest is defined as a classifier for classification purposes or a predictor for regression purposes, comprising the ensemble of single decision trees or regression trees (**Equation 5.1**).

$$\{h\ (\mathbf{x}, \boldsymbol{v_k}), k = 1, \ldots\} \qquad\qquad (\textbf{Equation 5.1})$$

For classification tasks, each decision tree casts a vote for a certain class label given input $\mathbf{x}$ and the classification of the random forest equals the class label that receives the most votes. Similarly, for regression tasks, the tree predictor $h\ (\mathbf{x}, \boldsymbol{v_k})$ bears numerical values instead of class labels and the prediction is made by calculating the mean smartphone sales of k trees $h\ (\mathbf{x}, \boldsymbol{v_k})$.

Tree Splitting Criteria

There are several try splitting algorithms such as C4.5 based on gain ratio and ID3 based on entropy. The R package *randomForest* used for this paper applies the CART algorithm (Breiman et al., 1984) that calculates the GINI index as the principle for impurity reduction when building decision trees, or the residual sum of squares (RSS) using the least squares method to determine the splits for regression trees. The mathematical expression of GINI is demonstrated by **Equation 5.2** where GI_k is the GINI of a tree node k with J levels of class labels – for this paper smartphone features - and p_i is the probability of certain classification i.

$$GI_k = 1 - \sum_{i=1}^{J} (p_i)^2 \qquad \textbf{(Equation 5.2)}$$

The model established for this paper is a random forest for regression which uses RSS as the splitting criterion for individual regression trees which were constructed via bootstrapping samples (different smartphone models) from the pre-processed *IDC Worldwide Smartphone Tracker Data* with replacement. Displayed in **Equation 5.3** where RSS_k is the residual sum of squares of a node k, n is the number of datapoints, $(y_i - \hat{y_i})^2$ represents squared residuals of predicted smartphone sales. The smartphone feature with the lowest RSS is selected as the split for this node.

$$RSS_k = \sum_{i=1}^{n} (y_i - \hat{y_i})^2 \qquad \textbf{(Equation 5.3)}$$

Bagging

If a statistical model absorbs the noise in the training data to make predictions, overfitting occurs. Bootstrapping the training data will prevent overfitting since the different noise information learnt in the individual trees will offset each other. When building a random forest, the training set is bootstrapped with replacement in the same size while letting each individual tree to grow as large as possible. Such bootstrap aggregation is called bagging (Breiman, 1996), which is one of the main advantages of random forests compared to individual regression or decision trees. In addition to bagging, random forests also add diversity to the individual trees by randomly selecting a number of smartphone features at split positions.

Tuning

According to Breiman (1996), the out-of-bag observations are the "built-in" testing set that comes with bagging and random forests. They refer to the observations that were left out in the bootstrap process. For this paper, they are the smartphone model observations that were not selected in the construction of individual trees. The out-of-bag (OOB) mean squared error (MSE) or OOB error is considered a fair means of model performance. There are two parameters of random forests that affect the performance of the results the most: the number of randomly selected smartphone features at split positions and the total number of trees. To tune these parameters[6], the square root of the total number of smartphone features is calculated and rounded to 4, designated as the starting value of the argument *mtry*. The algorithm scans both sides of the value 4 and obtains the optimal *mtry* value with the lowest OOB Error or RSS. Due to the large size of the data set and limited computational power of personal computers, tuning parameters of the RF model is not feasible for this paper.

The theoretical results of Breiman (1996) indicate that random forests do not overfit with an increasing number of trees. Several following studies have not excluded the possibility of overfitting in random forests. Generally speaking, raising the number of trees will not reduce prediction accuracy. That is to say, at a certain point, adding trees will also not improve model performance but drastically increase computational intensity.

Building a Random Forest with Regression Trees

A simplified procedure of how a random forest is built for regression purposes is described in the following steps:

1. Bootstrap with replacement from the data set to build individual regression trees.
2. Assign a random subset of variables at each tree split and use the lowest MSE of least squares as the principle for splitting.
3. Calculate the mean of the predictions made by the ensemble of individual trees.
4. The out-of-bag samples are used as a test set to calculate the MSE for the random forest as an indicator of model performance.

For this paper, the quarterly data of smartphone features and sales in a given year is fed to the RF model for training, generating the variable importance ranking of that year. This procedure is repeated for every year between 2004 to 2019 while the same treatment is also separately carried out for the six geographical regions in the world.

5.2 Variable Importance

As mentioned in section 3.4, I selected Random Forests, i.e., an embedded method, out of the 3 main categories of feature selection methods to generate feature importance ranking. More details are given in this section. Feature selection in parametric regression models is heavily influenced

[6] Help file of the software package *R*.

by the order of variables added or removed during the stepwise selection procedure. Similarly, feature selection in individual regression trees or decision trees are affected by the same order effect, causing the results to be unstable (Austin & Tu, 2004). The feature importance ranking generated by Random Forests - the approach used for this paper - proves to be more superior in terms of stability than parametric regression models (Rossi et al., 2005).

There are two measures of variable importance in Random Forests. First, the decrease in impurities (measured by GINI for classification and RSS for regression) of tree nodes split by a given smartphone feature is averaged over all the trees in the random forest. The second measure is more commonly applied: permute the values of a given smartphone feature from the out-of-bag observations, feed the permuted smartphone feature together with other intact smartphone features to the trained random forest model and calculate the increase in OOB error for classification or MSE for regression compared with when the given smartphone feature is unpermuted (Breiman, 2001). According to Strobl et al. (2009), the second measure is proven to be more advanced. The *randomForest* package in *R* allows the selection of one of these two measures. I select the second "permutation measure" which is also the software's default option for the analyses of this paper.

The "permutation measure" is defined as in **Equation 5.4** where $VI\ (X_k)$ is the importance of smartphone features (X_k) of a certain regression tree in the random forest, *n* is the number of out-of-bag observations (smartphone models) for this tree, $(y_i - \hat{y}_i)^2$ and $(y_i{}^p - \hat{y}_i{}^p)^2$ are residual sum of squares of smartphone model *i* before and after permutation.

$$VI_{tree}\ (X_k) = \sum_{i=1}^{n} \frac{1}{n}\ (y_i - \hat{y}_i)^2 - \sum_{i=1}^{n} \frac{1}{n}\ (y_i{}^p - \hat{y}_i{}^p)^2 \qquad (\textbf{Equation 5.4})$$

The raw importance score of smartphone feature (X_k) is calculated as the average importance score of (X_k) of all regression trees as demonstrated in **Equation 5.5** where *ntree* is the number of trees in the random forest.

$$VI_{raw}\ (X_k) = \frac{\sum_{t=1}^{ntree} VI_{tree}\ (X_k)}{ntree} \qquad (\textbf{Equation 5.5})$$

Eventually, the importance score as the output of the package *randomForest* is scaled via dividing the raw importance score by its standard deviation.

$$VI_{score}\ (X_k) = \frac{VI_{raw}\ (X_k)}{\frac{\hat{\sigma}}{\sqrt{ntree}}} \qquad \textbf{(Equation 5.6)}$$

For this paper, the mean importance scores from 2004 to 2019 of the all the smartphone features are calculated. Only the six smartphone features with the highest average importance scores are singled out and visualized. *Feature fatigue* can be identified when the importance score of a given feature exhibits a conspicuous decline - an elbow in the visualization. The specific relationships between the other important smartphone features and smartphone sales are analyzed via Partial Dependence Plots (PDP) which will be discussed in the next section.

5.3 Interpretation via Partial Dependent Plots (PDP)

In data science, interpretability is often compromised for higher prediction accuracy. In comparison with regression trees, there is no "typical" tree in a random forest that enables the interpretation of the model. Random forests are ensembles of different individual trees as a result of bootstrapping and random selections of variables at tree splits. It is inconceivable to visualize an average tree that represents the entire random forest. For this reason, random forests are considered black box models whose interpretations require model-agnostic techniques.

For this paper, obtaining feature importance scores alone does not present a complete picture of how important features cause *feature fatigue* in smartphone markets, because the importance scores do not depict how specifically the association between the features of interest and sales. For features that do not show a conspicuous decline in importance scores, model agnostic interpretations are required to further inspect if upgrading a given feature no longer boosts sales.

Model agnostic interpretations, as its name suggests, can be applied independently of the model. According to Ribeiro et al. (2016), there are three merits of model-agnostic interpretations: Model flexibility, explanation flexibility and representation flexibility. There are several frequently used model-agnostic interpretation techniques: partial dependence plot (PDP), individual conditional plot (ICE) and accumulated local effects plot (ALE). PDP reveals the marginal effect of an independent variable of interest on the dependent variable in a trained model (Friedman, 2001). According to Molnar (2020), the relationship PDP visualizes is on a global scale, compared with the local individual conditional effects revealed by ICE. This advantage enables ICE to capture the hidden heterogeneities ignored by PDP. Nevertheless, for this study, we are only interested in the effects of important smartphone features on sales in different markets holistically, instead of individual phone models. Therefore, detecting heterogeneity is redundant to the goal of this paper.

For the same reason, using ALE to deal with the other disadvantage of PDP which requires the assumption of features' independence is not necessary. As a result, I select the partial dependence plot (PDP) as the technique to identify the smartphone features causing *feature fatigue*.

The definition of PDP for regression is demonstrated in **Equation 5.7** where x_S is the smartphone feature of interest whose value is constant and x_C are the other smartphone features whose average expectation is calculated to obtain the marginal effect of x_S. **Equation 5.8** displays the Monte-Carlo method used for the estimation of $\hat{f}_{x_S}$: the marginal effect of a given smartphone feature on smartphone sales. Let *n* be the number of observations (smartphone models). x_{Ci} are all the smartphone features except for the one of interest.

$$\hat{f}_{x_S}(x_S) = E_{x_C}\left[\hat{f}(x_S, x_C)\right] = \int \hat{f}((x_S, x_C)\, d\mathbb{P}(x_C) \qquad (\textbf{Equation 5.7})$$

$$\hat{f}_{x_S}(x_S) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}(x_S, x_{Ci}) \qquad (\textbf{Equation 5.8})$$

6 Results

6.1 Developments of Smartphone Feature Importance

As mentioned above, to identify *feature fatigue*, we should first look for features that exhibit a sustained decline (elbow) in the importance scores. Next, for the other features, PDP is used to spot features whose upgrades no longer improve sales. The importance scores of all smartphone features for the global market are displayed in **Figure 6.1A**. In 2009, the importance scores of a number of smartphone features began rising rapidly. It is plausible that this is due to the release of the first iPhone in 2007, which marked the start of an era dominated by touch-screen smartphones.

The average importance scores of all smartphone features were calculated in the period between 2004 and 2019. **Figure 6.1B** separately lists the six smartphone features with the highest average importance scores (In a descending order): *Average Selling Price (ASP) - USD*, *Processor Speed – Ghz*, *Screen Size*, *Resolution*, *Camera Megapixel* and *RAM - GB*. It is worth noting that all of the

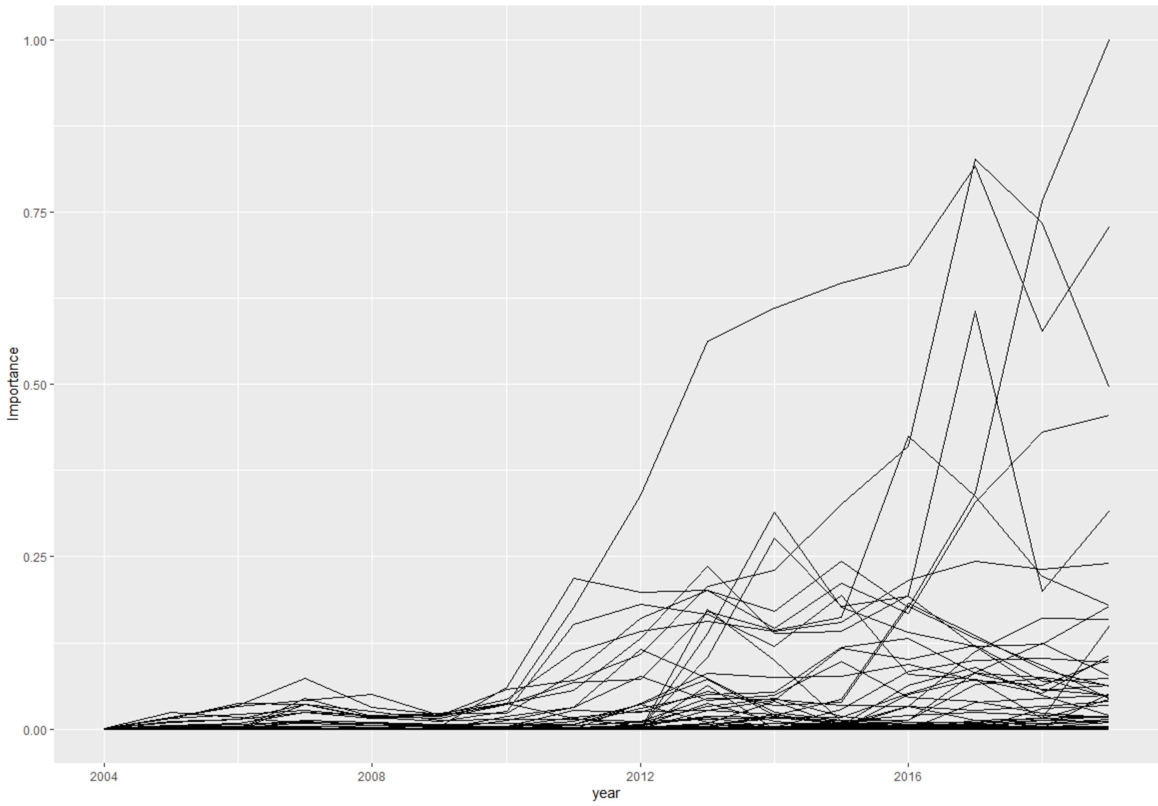


Figure 6.1A: Importance scores of all smartphone features between 2004 and 2019

features except for *ASP* are hardware smartphone features. As seen from **Figure 6.1B**, it is conspicuous that the importance of the most influential smartphone features on smartphone sales showed a drastic dip around the year of 2017. For market players, **Figure 6.1B** depicts a holistic global trend of the development of the top smartphone features' impact on sales, offering a tentative suggestion of features causing fatigue before we further explore the dynamics in the six regions.

As displayed in **Figure 6.1B**, in 2007 when iPhone was introduced, customer needs were altered and consequently exemplified in how they chose smartphones. Prior to 2007, smartphones were mainly used as a calling device. As of 2008 several other features start playing a role. First, the importance of *ASP* started becoming prominent and the high importance sustained. This is logical because smartphones initially became much more expensive than prior feature phones. When touch-screen smartphones gradually trickled down into the market along with the rise of the Android OS, there came the drastic rise of *Screen Size*, *Resolution*, *Processor Speed* and *RAM* (more apps, more need for memory). At last, the decline in the importance of *Resolution and Processor Speed* occurred due to demand saturation caused by *feature fatigue*.

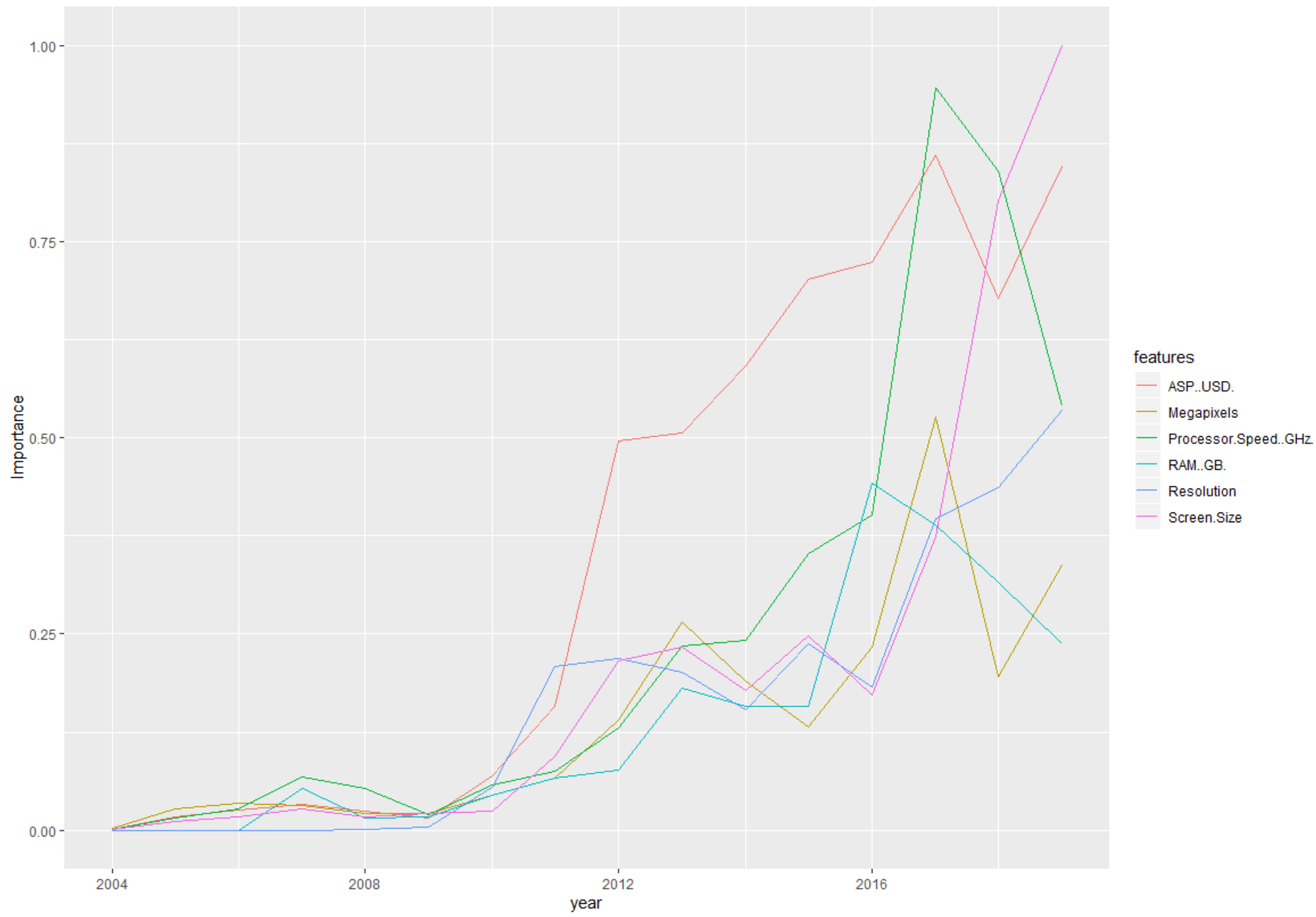


Figure 6.1B: six most important features in the world between 2004 and 2019

In practice, marketing strategies are designed at a much more micro level, such as for a specific region, country and/ or for a targeted market segment. The same random forest model established for the global market is separately run for the following regional markets: Western Europe, Central & Eastern Europe, Asia Pacific excluding Japan and the People's Republic of China (APeJC), USA, Latin America, Middle East & Africa. The top six smartphone features with the highest average importance scores are listed in **Table 6.1**.

Ranking / Region	1	2	3	4	5	6
Western Europe	Average Selling Price	OS - iOS	Resolution	Processor Speed	Screen Size	Fingerprint-Front
USA	Average Selling Price	OS - iOS	Resolution	Processor Speed	Storage	Fingerprint-Front
Central & Eastern Europe	Average Selling Price	Screen Size	Processor Speed	Storage	Cam Megapixel	Resolution
APeJC	Average Selling Price	Screen Size	Processor Speed	Resolution	Storage	Cam Megapixel
Middle East & Africa	Average Selling Price	Processor Speed	Screen Size	Storage	Resolution	RAM
Latin America	Average Selling Price	Processor Speed	DualSim - No	Screen Size	Resolution	RAM

Table 6.1: Regional rankings of the six smartphone features with the highest average importance

As displayed in **Table 6.1**, *Average Selling Price (ASP) - USD* is unsurprisingly the most impactful smartphone feature on sales across all six regions, maintaining the coherency to the findings of the global market - when it comes to purchasing a smartphone, consumers are most concerned about the price. In addition, the results in **Table 6.1** reveal resemblances between certain regions regarding important smartphone features: the rankings of the top 6 features are almost identical in Western Europe and USA except for the feature ranked 5th; Similarly, Middle East & Africa and Latin America share exactly the same important features except for rank 3 and 4 whereas the top 3 features in APeJC precisely match those of Central & Eastern Europe. This finding may be attributed to the similarities in income level, culture and demographics between these markets.

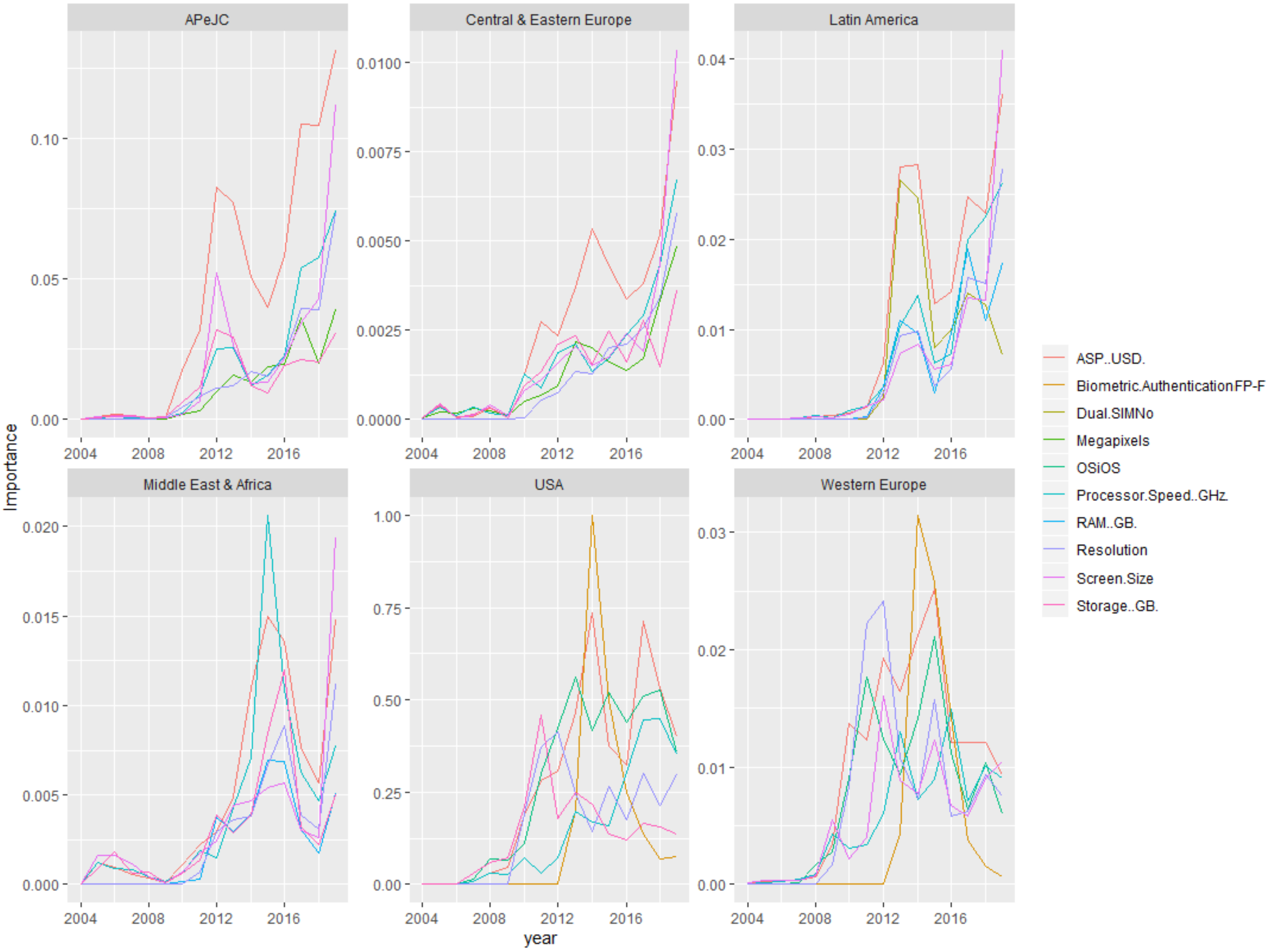


Figure 6.1C: most important features in each region between 2004 and 2019

Figure 6.1C demonstrates the developments of the importance scores of the most important smartphone features in the six regional markets between 2004 and 2019. As seen in **Figure 6.1C**, the importance scores of Western Europe and USA quickly started tipping upward after 2007, which is the year when the first iPhone was launched, enabling touch-screen smartphones to gain popularity and gradually sweep the industry afterwards. In comparison, the take-off of the importance scores occurred at a much later stage in other markets where iPhone's introduction and penetration were much slower – around 2009 in Central and Eastern Europe and APeJC, and around 2011 in Middle East & Africa and Latin America. The surging thrust of the importance scores in all six regions was met with a dip in the time period varying from 2011 to 2015. In Western Europe and USA, the downward trend sustained till 2019 and showed no sign of recovery, indicating that consumers in these two markets no longer put heavy emphases on hardware features when purchasing smartphones. For smartphone companies, modifying or upgrading hardware features may not generate as much sales growth in these markets as before. In April 2019, the two biggest telecom carriers in USA - Verizon and AT&T - released official data[7] indicating a record low frequency for American consumers to upgrade their smartphones. This trend is particularly pronounced in developed nations. In the other four less economically developed regions, the dip in the importance scores was reversed between 2015 and 2017, tilting the curves steeply upwards and the trend sustained until 2019 and is likely to continue thereafter.

Before I perform the first round of screening for *feature fatigue*, *Average Selling Price (ASP) - USD* will be excluded from the analyses since it is ranked the most important feature in the global market and all the six regions. The Partial Dependence Plots (PDP) between *Average Selling Price (ASP) - USD* and *Sales – Units* are displayed in **Figure 6.3** to **Figure 6.8** in the **Appendix**. A general negative association is detected across all the six regions – the higher the price, the lower the sales. When designing market strategies, pricing is known to be one of if not the most important factors. Including it will not produce incremental macro market insights to smartphone companies.

By examining **Figure 6.1C**, the sustained decline in importance scores or "elbow" can be recognized for *Processor Speed – Ghz*, *OSiOS, Resolution* and *Biometric Authentication Fingerprint - Front* in Western Europe; *Processor Speed – Ghz* and *OSiOS* in USA; *DualSim - No* in Latin America. After identifying these features as causing fatigue, in the following sections, I will zoom in on the 6 regional markets as mentioned above and inspect, among the rest of the features, which ones caused *feature fatigue* according to the PDPs corresponding to each region. Note that in equation 5.7 the PDP is defined as a function of a feature, which should be visualized as a single line. However, a considerable proportion of the samples in this data set are smartphone models with relatively very low sales, only visualizing the PDPs as single lines would make it unfeasible to observe the development of the relationship between a smartphone feature and sales. Therefore, I use scatterplots instead of single lines to visualize the PDPs. The limitation and improvement of this approach are explained in the discussion section of this paper.

[7] https://www.theverge.com/2019/5/17/18629003/us-phone-upgrades-apple-samsung-market

6.2 Western Europe

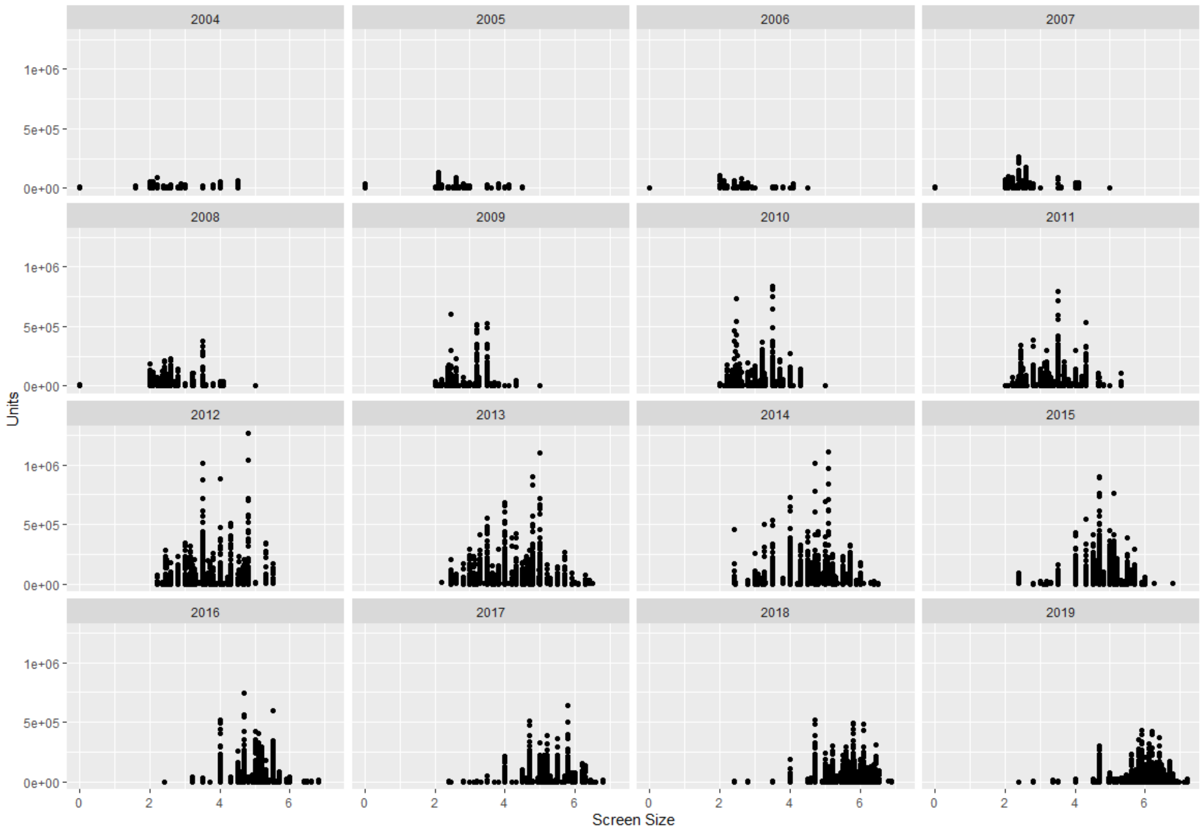


Figure 6.2A: Partial Dependence Plots (PDP) of *Screen Size* for Western Europe

Screen Size is Western Europe's only feature not eliminated in the first round of screening. **Figure 6.2A** reveals that as the screen sizes of smartphones got larger, the majority of sales gradually shifted from 3-inch phones to 5-inch phones between 2007 to 2017, and then from 5-inch phones to 6-inch phones from 2018 to 2019. Most of the sales went to the right side of the plot and somewhat stabilized. Maintaining the screen size around 6 inches appears to be a reasonable strategy to smartphone companies. Whether increasing screen sizes further would cause *feature fatigue* is inconclusive and debatable. I will revisit this feature in the following section.

6.3 USA

Figure 6.3A shows that the screen resolutions (in pixels) of smartphones were constantly being made higher thanks to advances in display technologies. Between 2010 and 2015, the newly introduced high-resolution smartphones were gaining considerable sales. This trend gradually diminished from 2016 to 2019, demonstrated by the obvious shrinkage in sales on the right sides of the PDPs, especially in 2019. This finding gives rise to the prospect that *Resolution* caused *feature fatigue.*

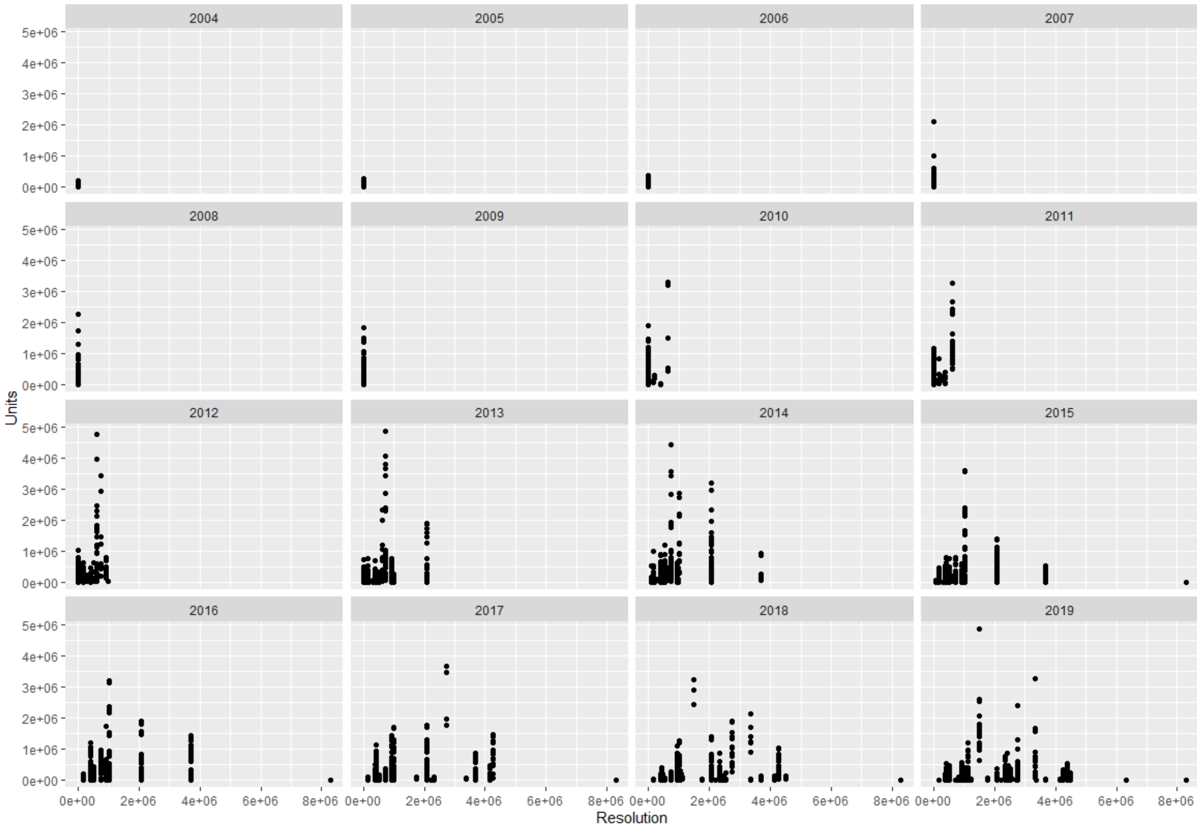


Figure 6.3A: Partial Dependence Plots (PDP) of *Resolution* for USA

As displayed in **Figure 6.3B**, sales mostly concentrated on smartphones with less than 120-GB storage prior to 2016, the emergency of models with 250-GB storage capacity between 2016 and 2017 and later 500 GB between 2018 and 2019 did reap some benefits as they recorded noticeable sales in these time periods. Even though sales of 500-GB smartphones declined in 2019 compared to 2018, the duration is not long enough to call it a sustained trend. Therefore, *Storge – GB* did not cause feature fatigue.

Figure 6.3C illustrates the comparisons of violin plots between *Biometric Authentication Fingerprint – Front* to other biometric authentication features of smartphones. In the early years after the front fingerprint sensor feature was introduced, its sales remained higher than all the other biometric authentication features. This advantage faded between 2017 and 2019. For the time-being, *Biometric Authentication Fingerprint-Front* is identified as a candidate for causing feature fatigue. We will come back and elaborate more on this feature and the other categorical feature *OSiOS*.

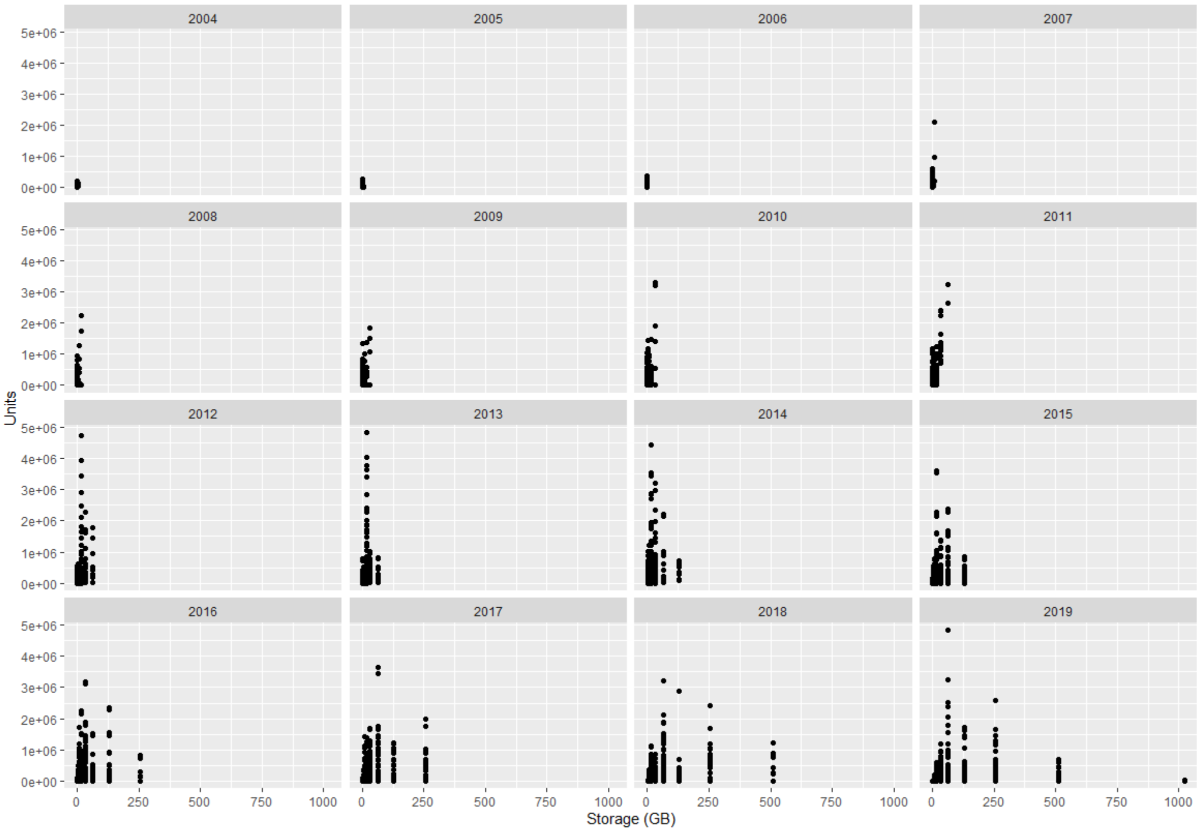


Figure 6.3B: Partial Depend Plots (PDP) of *Storage - GB* for USA

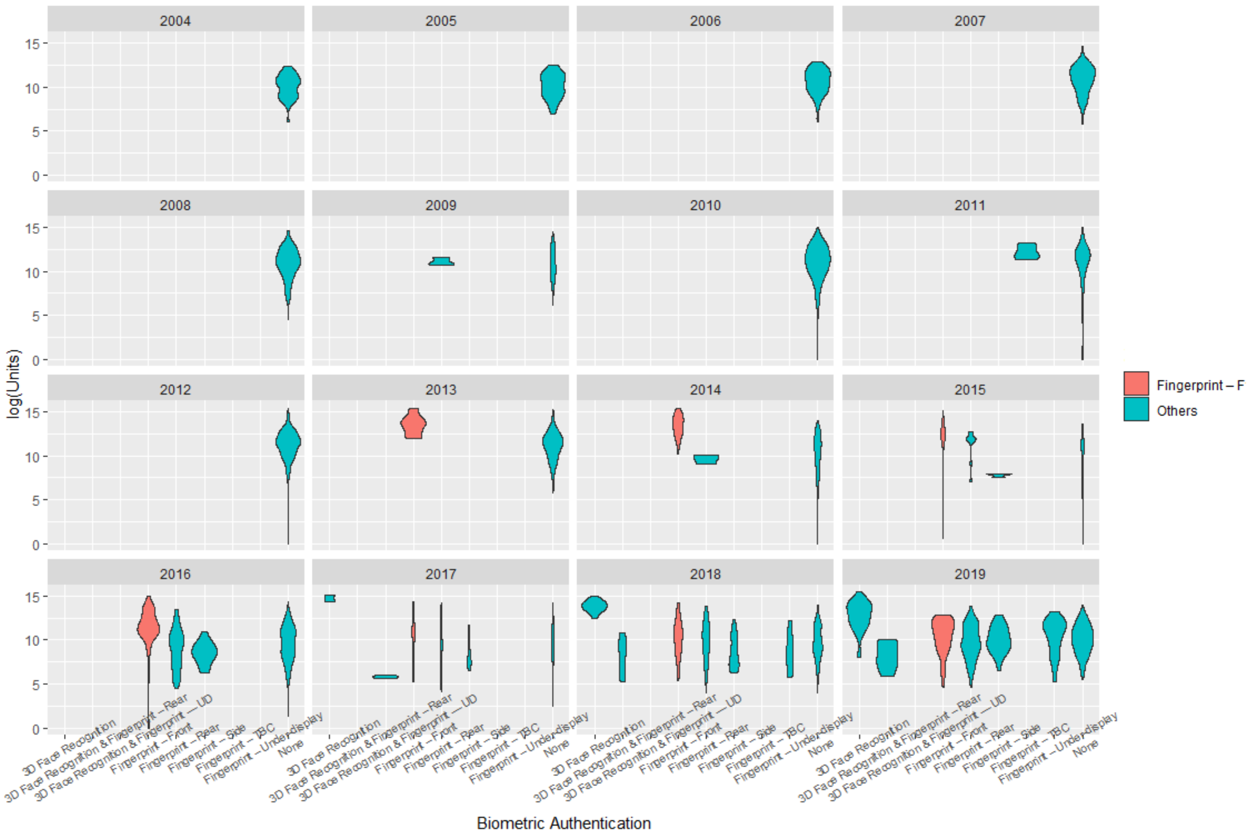


Figure 6.3C: Partial Dependence Plots (PDP) of *Biometric Authentication Fingerprint-F* for USA

6.4 Central & Eastern Europe

Figure 6.4A in the Appendix depicts a pattern similar to the findings of Western Europe. Whether increasing screen sizes caused *feature fatigue* is uncertain.

Figure 6.4B indicates that as the availability of the types of processors increased in the market, consumers also welcomed newer and more powerful processors. After 2017, sales moved to smartphones with higher-end processors and as the right side of the plots became more crowded - price reductions of high-end models likely also played a role. Evidently, *Processor Speed – Ghz* did not cause *feature fatigue*.

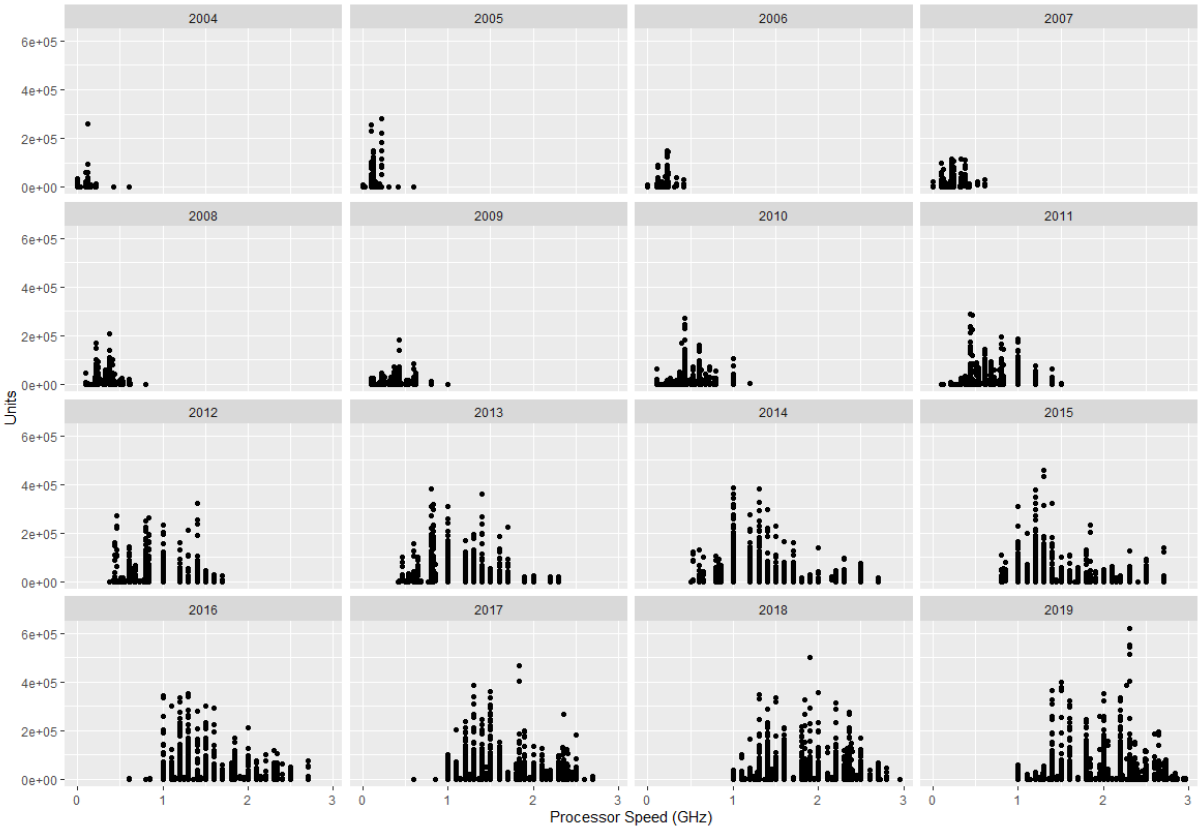


Figure 6.4B: Partial Dependence Plots (PDP) of *Processor Speed* for Central & Eastern Europe

As displayed in **Figure 6.4C**, the introduction of smartphones with storage larger than 250 GB in 2016 did not alter the market landscape, as the vast majority of sales lingered with devices equipped with less than 120 GB storage capacity despite the fact that models with larger storage had been available for years. *Storage – GB* definitely caused *feature fatigue*.

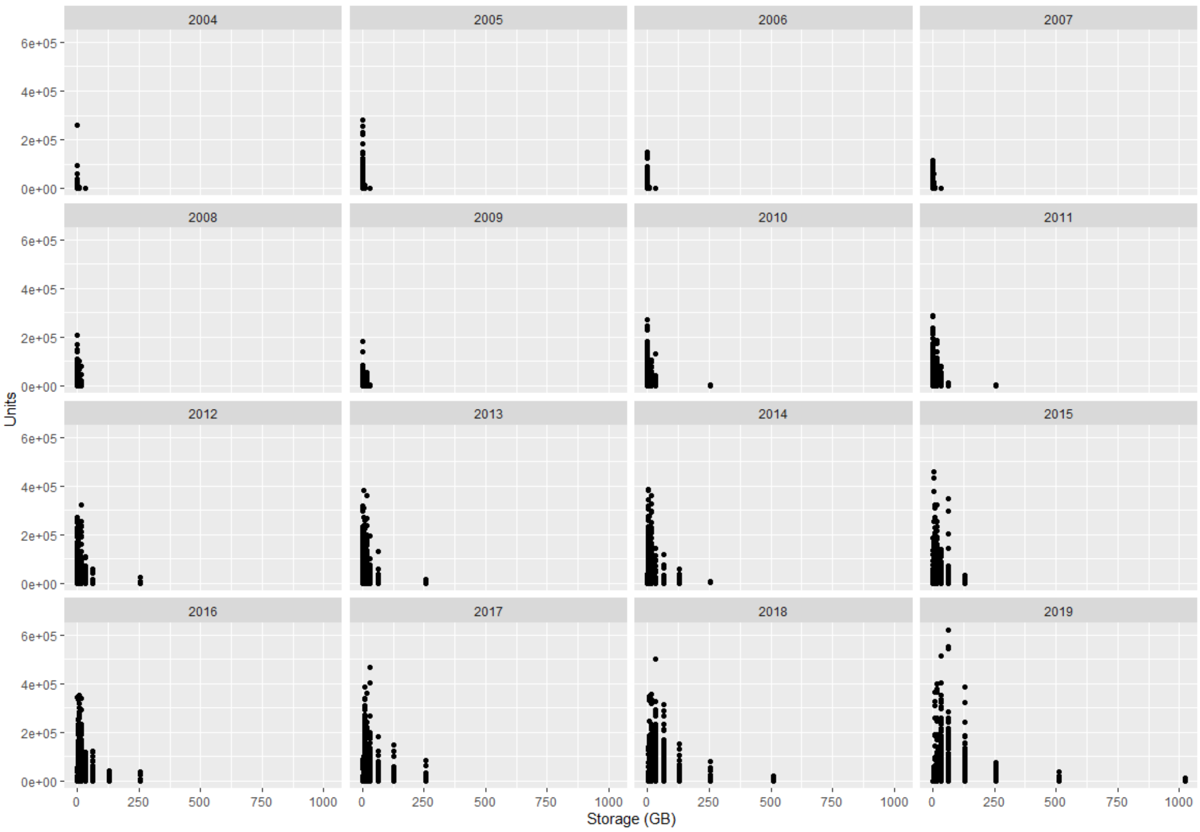


Figure 6.4C: Partial Dependence Plots (PDP) of *Storage - GB* for Central & Eastern Europe

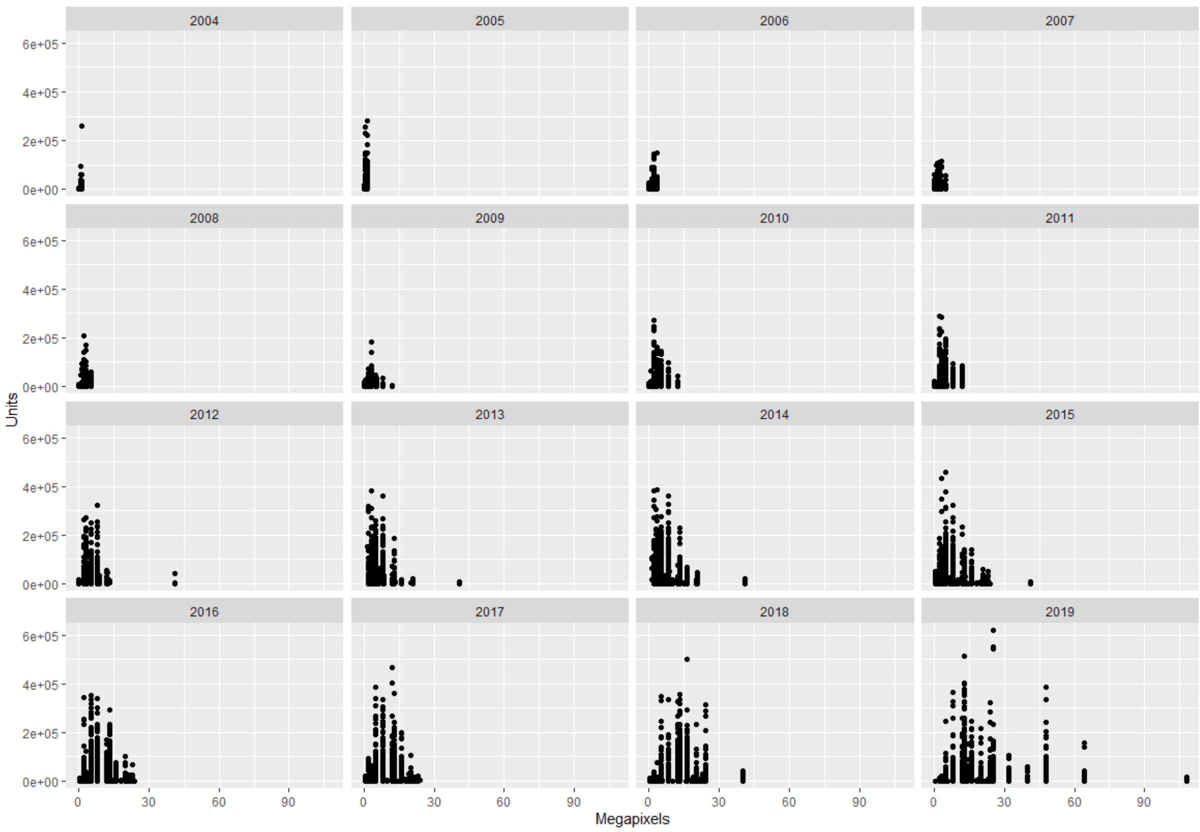


Figure 6.4D: Partial Dependence Plots (PDP) of *Megapixels* for Central & Eastern Europe

Figure 6.4D shows that before 2018, the majority of sales stabilized on smartphones with less than 30-megapixel cameras, in 2018 the introduction of phone cameras more powerful than 30 megapixels only harvested a small fraction of the market - likely photography fanatics. The year 2019 showcased a surprise as sales of smartphones with high-end cameras exploded. It is safe to conclude that *Megapixels* did not cause *feature fatigue*.

Figure 6.4E revealed that after 2012, the emergency of higher resolution smartphones slowly grabbed the attention of consumers and the momentum accelerated after 2017 when higher resolution phones recorded considerable sales, this trend may well continue after 2019. Henceforth, it would be more reasonable to observe the future development of this trend before identifying *Resolution* as causing *feature fatigue*.

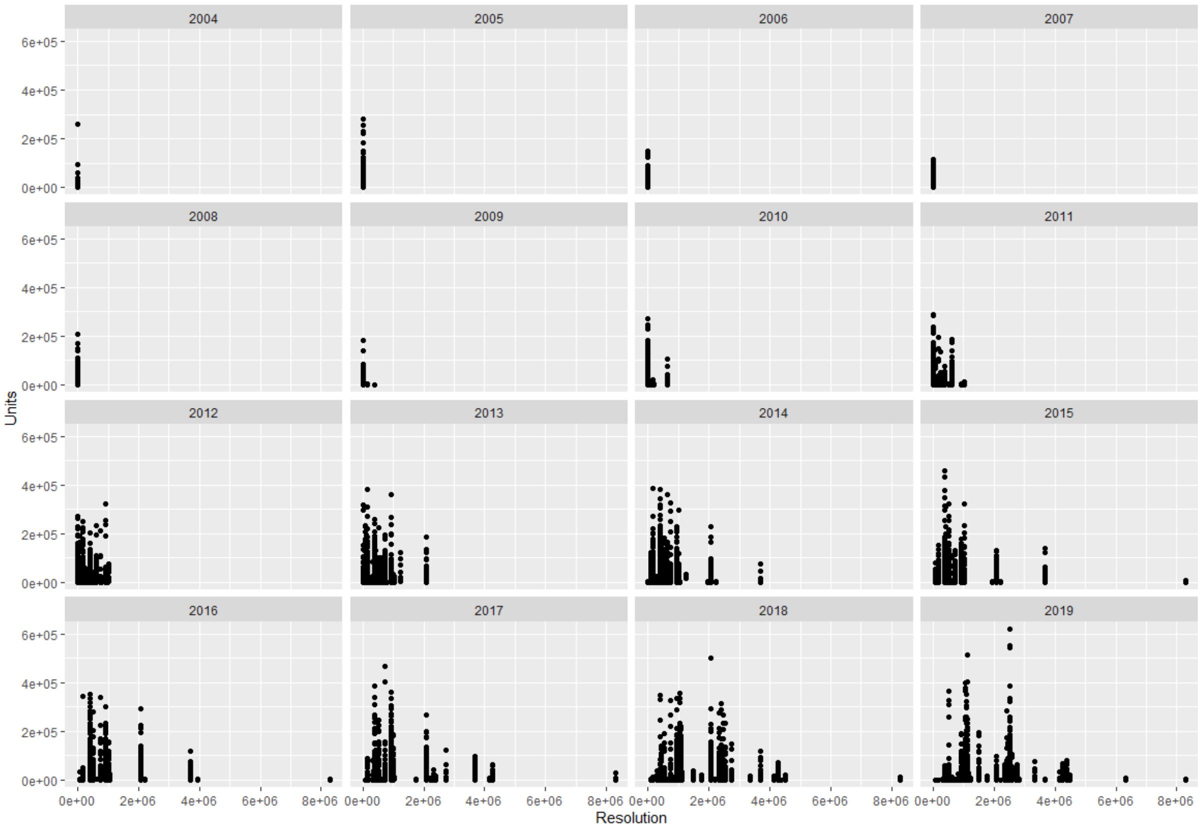


Figure 6.4E: Partial Dependence Plots (PDP) of *Resolution* for Central & Eastern Europe

6.5 Asia Pacific excluding Japan and China (APeJC)

Figure 6.5A, **Figure 6.5B** and **Figure 6.5C** in the Appendix exhibit similar patterns found in Central & Eastern Europe. Whether increasing screen sizes further would cause *feature fatigue* is inconclusive. *Processor Speed – Ghz* and *Resolution* did not cause *feature fatigue*.

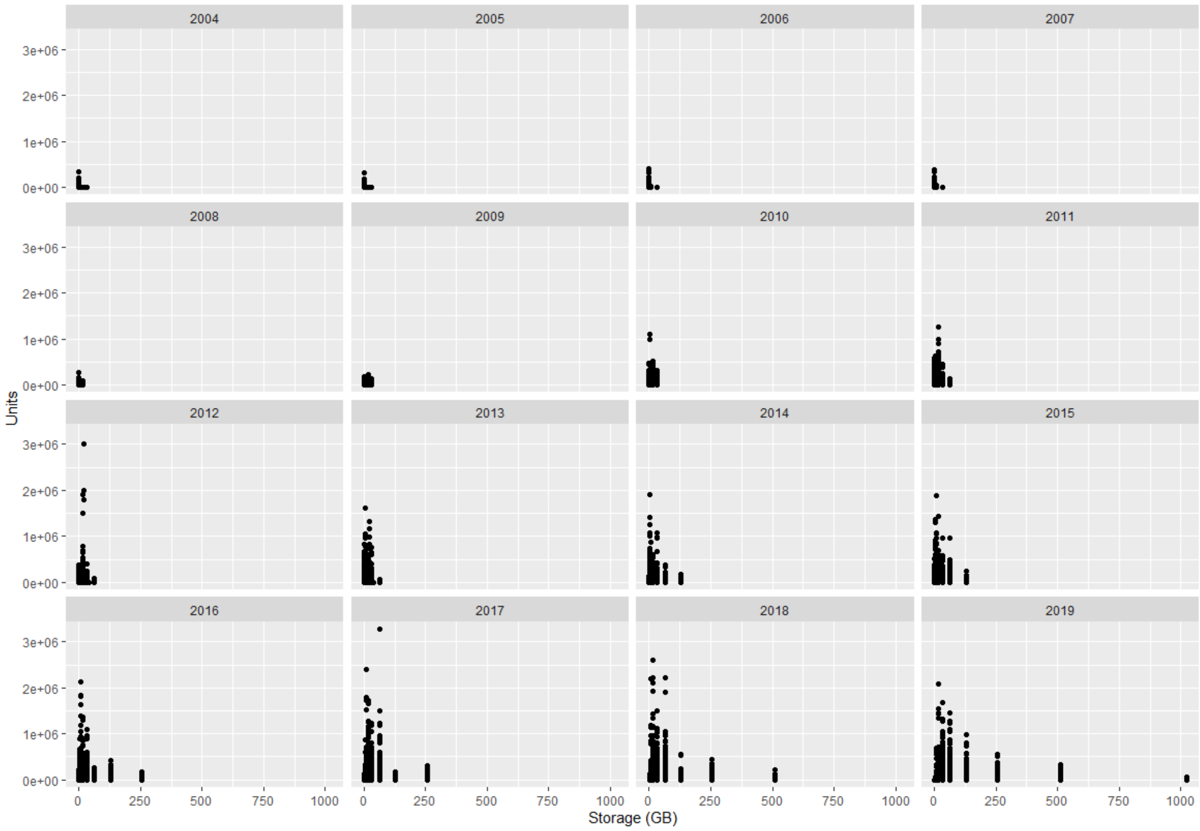


Figure 6.5D: Partial Dependence Plots (PDP) of *Storage* - *GB* for APeJC

There are slightly different dynamics for the feature *Storage – GB* compared to the findings in Central & Eastern Europe. As displayed in **Figure 6.5D**, when smartphones with larger storage capacity were launched in the market, the sales of 250-GB and 500-GB models seem to be gaining momentum after 2016. It would be sensible to observe the development of this trend. It is inconclusive whether or not *Storage – GB* caused *feature fatigue*.

Figure 6.5E in the Appendix exhibits a resemblance to the findings in Central & Eastern Europe. It is inconclusive to identify Megapixels as causing *feature fatigue*. It remains to be uncovered whether consumers will keep pursing better smartphone cameras.

6.6 Middle East & Africa

According to **Figure 6.6A**, higher speed processors enjoyed substantial growth between 2012 and 2015. The momentum showed signs of diminishing as the sales of high-end models flattened from 2016 to 2018. However, sales appeared to be lifted again in 2019 for mid to high end models. It would be imprudent to classify *Processor Speed – Ghz as* causing *feature fatigue*.

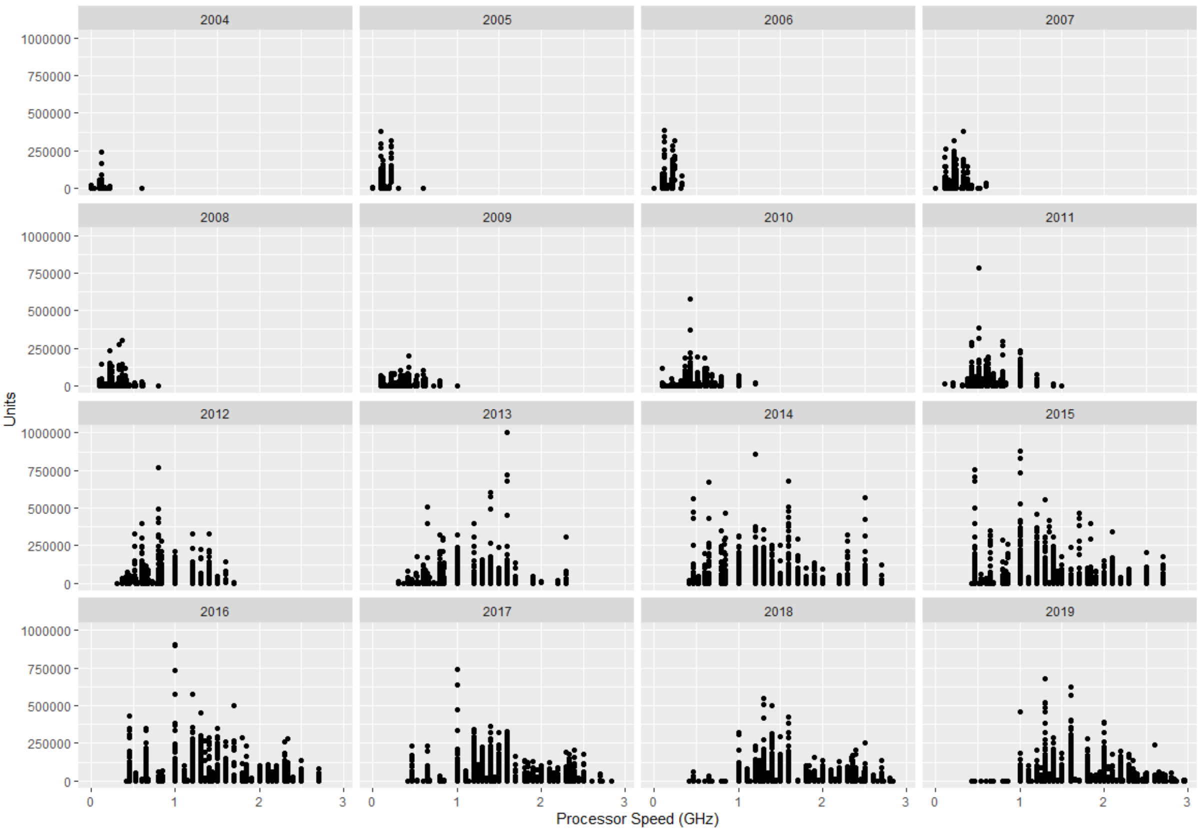


Figure 6.6A: Partial Dependence Plots (PDP) of *Processor Speed – Ghz* for Middle East & Africa

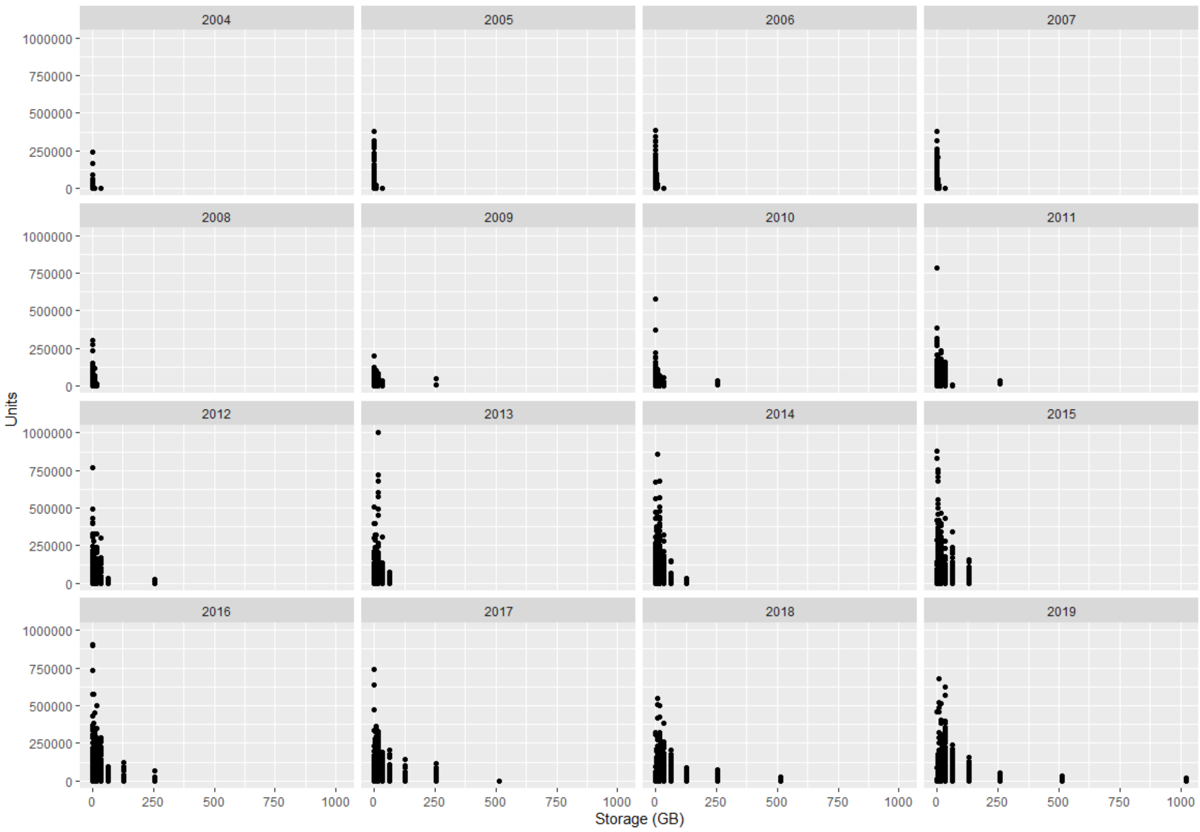


Figure 6.6C: Partial Dependence Plots (PDP) of *Storage - GB* for Middle East & Africa

Similar to what is found in Central & Eastern Europe**, Figure 6.6B** in the Appendix portrays a clear trend that the majority of sales shifted from 4-inch devices in 2014 to 6-inch ones in 2019. Thus, *Screen Size* do not cause *feature fatigue*.

Figure 6.6C indicates that smartphones with larger than 120-GB storage capacity struggled to gain popularity despite being available in the market for years. Moreover, 250 GB and 500GB devices even showed signs of decline in the years leading to 2019. A tentative conclusion can be drawn that *Storage – GB* caused *feature fatigue*.

As demonstrated in **Figure 6.6D**, high-resolution smartphones became increasingly accepted by the market during the years between 2012 and 2017. Even though this transition appears to be unstained in 2018 and 2019. But the duration of the trend is too short to identify *Resolution* as causing *feature fatigue*.

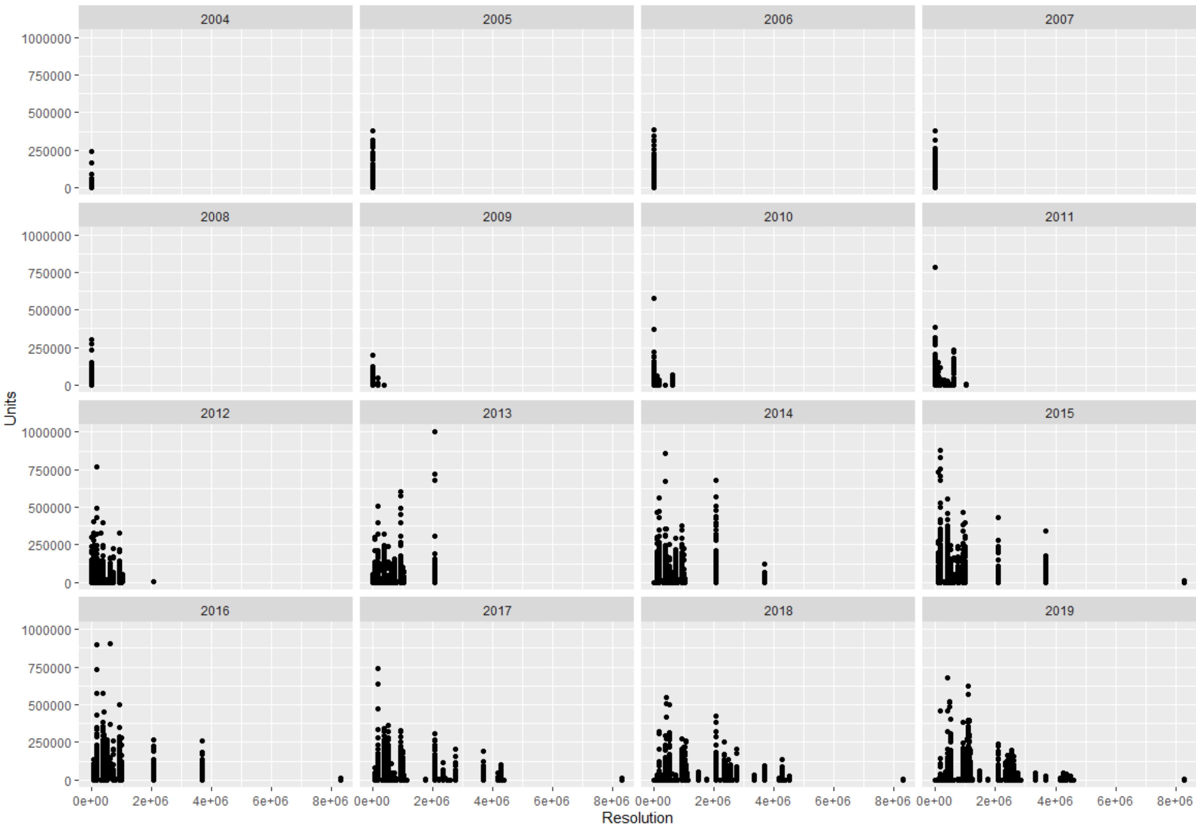


Figure 6.6D: Partial Dependence Plots (PDP) of *Resolution* for Middle East & Africa

In **Figure 6.6E**, consumers showed quick approval to smartphones with higher RAM whenever upgraded models entered the market. This trend was consistent between 2012 and 2018. In 2018 and 2019, even when devices with far more superior RAM were introduced, sales continued to grow. Accordingly, *RAM – GB* did not cause *feature fatigue*.

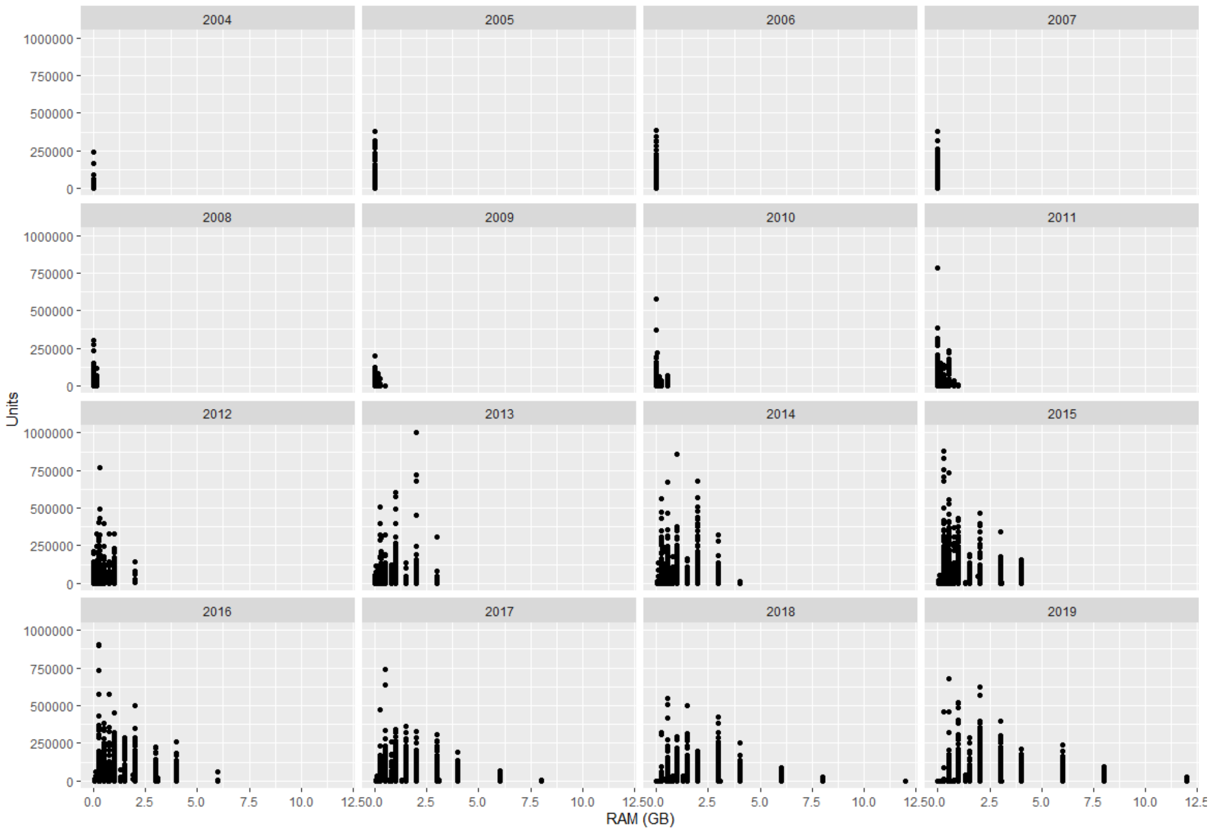


Figure 6.6E: Partial Dependence Plots (PDP) of *RAM -GB* for Middle East & Africa

6.7 Latin America

Figure 6.7A in the Appendix outlines a similar and conspicuous tendency found in Central & Eastern Europe. It is inconclusive to label *Screen Size* as causing *feature fatigue*. **Figure 6.7B** and **Figure 6.7C** in the Appendix depict similar trends found in Middle East & Africa. *Processor Speed – Ghz* and *Resolution* did not cause *feature fatigue*. The plots **In Figure 6.7D** in the Appendix are nearly identical to the ones of Middle East & Africa. *RAM – GB* did not cause *feature fatigue*.

7 Conclusion & Discussion

Table 7.1 provides a summary of the smartphone features causing *feature fatigue* in each of the 6 regional markets. Western Europe and USA are the two regions that have the most features causing fatigue while their results are exactly identical. Central & Eastern Europe, Middle East & Africa and Latin America each has one feature causing fatigue while APeJC has none. The clear distinction between Western Europe, USA and the other four markets may be attributed to differences in income level, culture and demographics between them. Consumers in high-income regions as Western Europe and USA exhibit feature fatigue more rapidly and intensively.

Region	Features Causing Feature Fatigue			
Western Europe	OS - iOS	Processor Speed	Resolution	Biometric Authentication Fingerprint - F
USA	OS - iOS	Processor Speed	Resolution	Biometric Authentication Fingerprint - F
Central & Eastern Europe			Storage	
APeJC			N/A	
Middle East & Africa			Storage	
Latin America			DualSim - No	

Table 7.1: features causing feature fatigue in the 6 regional markets

Amongst the features presented in **Table 7.1**, *Resolution*, *Processor Speed* and *Screen Size* coincide with the findings from the global market as a whole. Consumers may find higher resolutions increasingly redundant as the incremental utilitarian gain in viewing experience diminishes. Ultra-powerful processors exceed the daily usage needs of most consumers with the exception of a niche market for smartphone gamers. It is worth noting that whether *Screen Size* truly causes *feature fatigue* is debatable. In the PDPs presented in the result section, sales shifted to smartphones with a screen size of around 6 inches in the years approaching 2019, which makes it tempting to draw a conclusion that this feature does not cause *feature fatigue*. However, due to the biological limitation of the human palm size, whether making larger than 6-inch devices would lure consumers to these models is uncertain, especially because the vast majority of smartphone models offered in the market have a screen size of less than 7 inches. *Screen Size* may cause *feature fatigue* not because consumers consider large displays superfluous, but rather they might find these models physically cumbersome to use – damaging the utilitarian value of the device in the long term, which fits the definition of *feature fatigue*.

OS – iOS and *Biometric Authentication Fingerprint-F* are categorical features. As demonstrated in the PDPs (**Figure 6.3C** in the result section and **Figure 7.1** in the **Appendix**), sales of smartphones with these two categorical features started declining in the years approaching 2019. This is more likely due to, instead of *feature fatigue*, the introduction of a number of other categorical features into the market. For instance, in 2016 the emergency of other biometric authentication features such as facial recognition is a direct cause for the decline in the market share of smartphones with fingerprint sensors. Similarly, other competing operating systems such as Android may be the reason for observing a negative association between *OS -iOS* and sales. When using the feature importance generated by Random Forests to detect *feature fatigue*, prudency is required to scrutinize categorical variables even when the PDP of a feature indicates *feature fatigue*. On the contrary, while also being a categorical feature, *DualSim - No* in Latin America indeed caused feature fatigue. It was identified in the first round because the steep decline in the importance score indicated that this feature's impact on sales diminished. At first glance, not having the Dual-Sim functionality as a cause of *feature fatigue* may seem counter-intuitive. In the context of the Random Forest algorithm, permuting the values of *DualSim - No* causes less increase in MSE compared to the base level of this categorical variable. That is to say, having standby modes other than Dual-Sim no longer affects smartphone sales.

After excluding *OS – iOS* and *Biometric Authentication Fingerprint-F* from **Table 7.1**, all the features causing fatigue are hardware smartphone features. It is logical since adding hardware features is more likely to increase the price of the smartphone model and therefore, affect consumers' preferences. For smartphone companies, enhancing these hardware features would not significantly increase sales. Developing features that cater to the landscape in each market is a suitable strategy. For instance, a Chinese smartphone manufacturer Tecno Mobile developed a smartphone exclusively for the sub-Saharan African market with a camera focus feature that makes dark skin complexion more visible in poor light conditions. This model quickly became one of the best-sellers.

There is an unneglectable shortcoming in the *IDC Worldwide Quarterly Mobile Phone Tracker* used for this paper: battery life, a crucial feature weighed by consumers when purchasing a smartphone, is not included in the data provided. A survey[8] carried out by *YouGov Omnibus* in 2018 found that 41 % of US smartphone users consider batter life as their most vital smartphone feature.

There is an assumption in this study that the introduction of a new feature is positively associated with sales because theoretically, a smartphone feature can have a high importance score while being negatively associated with sales. This scenario is more likely to occur with categorical variables because generally speaking for numerical variables, more is better. To eliminate the small possibility of mistakenly identifying such a smartphone feature as causing fatigue, a more prudent scrutinization should be applied so that the plot of importance scores must always be followed by the inspection of the PDP to ensure the relationship is positive.

An important limitation of the paper lies in the approach used to visualized the PDPs. The majority of the samples in the data set are smartphone models with relatively very low sales which would pull the lines in the PDPs towards the bottom of the plots, making it unfeasible to observe any pattern. Scatterplots are used instead to detect the developments of the relationships between

[8] https://today.yougov.com/topics/technology/articles-reports/2018/02/20/smartphone-users-still-want-longer-battery-life

smartphone features and sales. The shortcoming of this method is that the data points in the PDPs would overlap, thus rendering the plots unable to reveal the true "density" of sales. For scholars who intend to carry out a more polished version of this study, a potential solution is to assign each sample a weight proportional to its sales when generating the PDPs.

Due to the limitation in the computational capacity of personal computers, the random forest model created for this paper was executed without tuning the parameters. Ideally, tuning should be performed in cloud servers that can handle such large-scale data. Nevertheless, this paper has established a framework for more deliberate analyses of *feature fatigue* targeting a specific market segment such as photography phones or business phones for a certain region or country.

In general, scientific disciplines such as physics, chemistry and biology seek to make inquisitions, gain knowledge and prove causation by conducting parallel experiments with all variables being the same except for the variable(s) whose effects are to be investigated. Whether causation can be established is by altering the variable(s) in question while holding the other variables constant. By replicating two parallel experiments in a laboratory environment, it allows the controlling for all possible variables. For instance, the double-blind experiments in the medical industry. Unfortunately for social science disciplines, such an approach is impossible to implement because markets, industries, countries or companies cannot be replicated in a laboratory environment for a double-blind experiment to control for all variables (Diamond, 1998). Consequently, it is infeasible to include all the variables potentially influencing smartphone sales. The findings of this paper do not prove causalities between smartphone features and sales.

Despite not being able to reproduce a lab environment to prove causality, a similar experiment to the double-blind test in a micro phone-model setting (meaning not considering macro-economic variables such as GDP growth) can be designed for future studies to more precisely measure the effects of smartphone's features on sales using the concept borrowed from Propensity Score Matching. PSM is a statistical method widely used for estimating the causal treatment effects (Alberto & Imbens, 2016). In the context of this paper, for simplicity, suppose the treatment is a continuous variable *Storage*. First, place all the observations in a multi-dimensional space created based on all smartphone features besides *Storage* and the dependent variable *Sales.* Next, select a random observation as the centroid and define a radius to create a neighborhood. Then calculate the distances between the observations within this neighborhood. Repeat this procedure several times (ideally until all observations are covered if computational capacity allows) and choose the neighborhood with the lowest sum of distances. The observations (phone models) in this neighborhood are theoretically identical except for their *Storage* and *Sales*. Then, feed these observations while including *Storage* and *Sales* to a prediction algorithm such as OLS or RF (training set). Use the same method to select another neighborhood with the lowest sum of distances as the testing set and train it. Eventually, the treatment effect would be quantified as the parameters in OLS and causality would be proven if the parameters are identical in the training and testing sets.

According to Kaplan (1964), "Generalization must be truly universal, unrestricted as to time and space. It must formulate what is always and everywhere the case, provided only that the appropriate conditions are satisfied." This notion describes the widely accepted belief that discredits the value of scientific research projects aimed at the particular rather than the general. Nonetheless, establishing generalization in social sciences may be challenging. Cronbach (1975) stated that "propositions describing atoms and electrons have a long half-life, and the physical theorist can regard the processes in his world as steady. Rarely is a social or behavioral phenomenon isolated enough to have this steady-state properly." Does research in the realm of social sciences comply with the definition of generalization? We can at least say that there is no absolute generalization. An ongoing example can be given about the believes in the relationship between interest rate and inflation. According to classical economics theories, lower interest rate leads to higher inflation. Today, the contradictory Neo-Fisherian theory emerged in an era of unprecedented negative interest rates in in Japan and the Euro-Zone as a result of the central banks' inability to lift inflation.

According to classical statistics theories, generalization refers to the inference about the parameters of the population derived from sampled data (Jaynes, 2004). The distribution of a given population can be established by mainly three methods: theoretical distributions derived from parameter estimations and under assumptions, empirical distributions derived from resampling methods such as bootstrapping, and posterior distributions derived from the Bayesian framework (Kruschke, 2010). The advances in computing power and disk storage capacity along with the emergence of machine learning have made studies of large-scale data feasible. In the context of this paper, while deriving insights from the IDC data set is the objective, the problem of generalization cannot be ignored. Machine learning treats the model performance indicator – generalization error – as an approximation to the loss function (in the training set). Because the generalization error does not monotonically decrease with the training set prediction error, model validation is required to prevent overfitting and to evaluate model performance on observations outside of the sampled data. In RF, this process is performed via out-of-bag samples. Bootstrapping is a method used for approximating the standard errors of validity generalization estimates (Switzer et al.,1992). It is used to construct individual trees in RF, which is one of the reasons why RF is considered to generalize well. The results of the random forest model in this paper are stable, enabling it to have excellent generalization ability. The difference from classical statistics is that the distributions of the importance scores are unknown, thus no confidence intervals can be provided.

For this study, to compare importance scores in different years, an assumption is introduced that the average sales per smartphone model of a given region does not fluctuate over time. Since the distributions of the importance scores are unknown, this can be considered a limitation of the study. Nadeau and Bengio (2003) and Markatou (2005) attempted to theoretically investigate this issue by repeatedly running the learning algorithm in order to obtain the variance and produce the confidence intervals under the assumption of the estimator having a normal distribution. This method can be used to verify that the importance scores are statistically significant in order to provide a solid theoretical foundation for them to be compared over time. The execution would certainly require the computing power of cloud servers.

References

Abadie, Alberto, and Guido W. Imbens. "Matching on the Estimated Propensity Score." *Econometrica*, vol. 84, no. 2, 2016, pp. 781–807.

Archer, K. J., & Kimes, R. V. (2008). Empirical characterization of random forest variable importance measures. *Computational Statistics & Data Analysis*, 52(4), 2249-2260.

Austin, P. C., & Tu, J. V. (2004). Automated variable selection methods for logistic regression produced unstable models for predicting acute myocardial infarction mortality. *Journal of Clinical Epidemiology*, 57(11), 1138-1146.

Breiman, L., Friedman, J.H., Olshen, R.A., & Stone, C.J. (1984). *Classification and Regression Trees*. New York, USA: Chapman and Hall.

Breiman, L. (1996). Bagging predictors. *Machine Learning*, 24(2), 123-140.

Breiman, L. (2001). *Random Forests. Machine Learning*, 45, 5–32.

Breiman, L. (2004). *Consistency for a simple model of random forests*. University of California at Berkeley, Technical Report 670.

Brown, C., & Carpenter, G. (2000). Why Is the Trivial Important? A Reasons-Based Account for the Effects of Trivial Attributes on Choice. *Journal of Consumer Research*, 26(4), 372-385.

Budescu, D. V. (1993). Dominance analysis: A new approach to the problem of relative importance of predictors in multiple regression. *Psychological Bulletin*, 114(3), 542-551.

Coad, A. (2009). *The growth of firms: A survey of theories and empirical evidence*. Cheltenham, UK: Edward Elgar Publishing.

Crick, F., & Koch, C. (2003). A framework for consciousness. *Nature Neuroscience*, 6(2).

Cronbach, L. J. (1975). Beyond the two disciplines of scientific psychology. *American Psychologist*, 30(2), 116–127.

Couper, M. P. (2000). *Web Surveys: A Review of Issues and Approaches.* Public Opinion Quarterly, 64(4), 464-494.

Diamond, J. (1997), *Guns, Germs and Steel* (2017 ed., pp. 426-430). London, UK: Penguin Random House.

Diaz-Uriarte, R., & Andres, A. (2006). Gene selection and classification of microarray data using random forest. *BMC Bioinformatics*, 7(3).

Fernández-Delgado, M., Cernadas, E., Barro, S., & Amorim, D. (2014). Do we Need Hundreds of Classifiers to Solve Real World Classification Problems? *The Journal of Machine Learning Research*, 15, 3133-3181

Fontana, J. M., Farooq, M., & Sazonov, E. (2013). Estimation of feature importance for food intake detection based on Random Forests classification. *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*.

Friedman, J. H. (2001). Greedy Function Approximation: A Gradient Boosting Machine. *Annals of Statistics*, 29(5), 1189 - 1232

Genuer, R., Poggi, J., & Tuleau-Malot, C. (2010). Variable selection using random forests. *Pattern Recognition Letters*, 31(14), 2225-2236.

Green, P. E., Krieger, A. M., & Wind, Y. (2001). Thirty Years of Conjoint Analysis: Reflections and Prospects. *Interfaces*, 31(3 - Supplement), 56-73.

Gregorutti, B., Michel, B., & Saint-Pierre, P. (2017). Correlation and variable importance in random forests, *Statistics and Computing*, 27, 659–678.

Grömping, U. (2007). Estimators of relative importance in linear regression based on variance decomposition. *The American Statistician*, 61(2), 139-147.

Grömping, U. (2009). Variable importance assessment in regression: Linear regression versus random Forest. *The American Statistician*, 63(4), 308-319.

Guyon, I., & Elisseeff, A. (2003). An introduction to variable and feature selection. *Journal of Machine Learning Research*, 3, 1157–1182.

Hoyle, B., Rau, M. M., Zitlau, R., Seitz, S., & Weller, J. (2015). Feature importance for machine learning redshifts applied to SDSS galaxies. *Monthly Notices of the Royal Astronomical Society*, 449(2), 1275-1283.

Iannario, M., Manisera, M., Piccolo, D., & Zuccolotto, P. (2012). Sensory analysis in the food industry as a tool for marketing decisions. *Advances in Data Analysis and Classification*, 6(4), 303-321.

Ishwaran, H. (2007). Variable importance in binary regression trees and forests. *Electronic Journal of Statistics*, 1(0), 519-537.

Jaynes, E. T., & Bretthorst, G. L. (2019). *Probability theory: the logic of science (pp. 76-77).* Cambridge University Press.

Kalousis, A., Prados, J., & Hilario, M. (2006). Stability of feature selection algorithms: A study on high-dimensional spaces. *Knowledge and Information Systems*, 12(1), 95-116.

Kaplan, A. (1964). *The Conduct of Inquiry: Methodology for Behavioral Science (pp. 91)*. San Francisco, USA: Chandler.

Keijzers, J., Ouden, E. D., & Lu, Y. (2008). Usability benchmark study of commercially available smart phones. *Proceedings of the 10th International Conference on Human Computer Interaction with Mobile Devices and Services - MobileHCI '08.*

Kohavi, R., & John, G. H. (1997). Wrappers for feature subset selection. *Artificial Intelligence*, 97(1-2), 273-324.

Kruschke, J. K. (2015). *Doing Bayesian data analysis: a tutorial with R, Jags, and stan (pp. 658-676)*. Elsevier, Academic Press.

Kühn, S., Strelow, E., & Gallinat, J. (2016). Multiple “buy buttons” in the brain: Forecasting chocolate sales at point-of-sale based on functional brain activation using fMRI. *NeuroImage*, 136, 122-128.

Lazar, C., Taminau, J., Meganck, S., Steenhoff, D., Coletta, A., Molter, C., de Schaetzen, V., Duque, R., Bersini, H., & Nowé, A. (2012). A survey on filter techniques for feature selection in gene expression microarray analysis. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 9(4), 1106-1119.

Li, J., Cheng, K., Wang, S., Morstatter, F., Trevino, R. P., Tang, J., & Liu, H. (2017). Feature Selection: A Data Perspective*. ACM Computing Surveys*. 50 (6), Article 94.

Li, M., & Wang, L. (2011). Feature fatigue analysis in product development using Bayesian networks. *Expert Systems with Applications*, 38(8), 10631-10637.

Markatou, M., Tian, H., Bisuas, S. and Hripcsak, G. (2005). Analysis of the variance of cross validation estimators of the generalization error of computer algorithms. *Journal of Machine Learning Research*, 6, 1127-1168.

Martilla, J. A., & James, J. C. (1977). Importance-Performance Analysis. *Journal of Marketing*, 41(1), 77-79

Molnar, C. (2020). Model-Agnostic Methods. In *INTERPRETABLE MACHINE LEARNING* (pp. 82-85). LULU COM.

Nadeau, C., & Bengio, Y. (2003). Inference for the Generalization Error. *Machine Learning*, 52, 239–281.

Reid, A. J. (2018). *The Smartphone Paradox: Our ruinous dependency in the device age*. Conway, USA: Palgrave Macmillan.

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Model-Agnostic Interpretability of Machine Learning. *ICML Workshop on Human Interpretability in Machine Learning*, No. Whi.

Rossi, A., Amaddeo, F., Sandri, M., & Tansella, M (2005). Determinants of once-only contact in a community-based psychiatric service. *Social Psychiatry and Psychiatric Epidemiology*, 40(1), 50–56.

Saeys, Y., Inza, I., & Larranaga, P. (2007). A review of feature selection techniques in bioinformatics. *Bioinformatics Review*, 23(19), 2507–2517.

Saeys, Y., Abeel, T., & Peer, Y. V. (2008). Robust Feature Selection Using Ensemble Feature Selection Techniques. *Machine Learning and Knowledge Discovery in Databases Lecture Notes in Computer Science*, 313-325.

Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods*, 14(4), 323–348.

Thompson, D. V., Hamilton, R. W., & Rust, R. T. (2005). Feature fatigue: When product capabilities become too much of a good thing. *Journal of marketing research*, 42(4), 431-442.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Scociety*, 58(1), 267-288.

Venkatesh, B., & Anuradha, J. (2019). A Review of Feature Selection and Its Methods. *Cybernetics and Information Technologies*, 19(1)

Wu, M., & Wang, L. (2011). Feature fatigue analysis based on behavioral decision making. 2011 IEEE International Conference on Industrial Engineering and Engineering Management.

Wu, M., Wang, L., Li, M., & Long, H. (2014). An approach of product usability evaluation based on Web mining in feature fatigue analysis. *Computers & Industrial Engineering*, 75, 230-238.

Zhao, Z., Anand, R., & Wang, M. (2019). Maximum Relevance and Minimum Redundancy Feature Selection Methods for a Marketing Machine Learning Platform. *2019 IEEE International Conference on Data Science and Advanced Analytics (DSAA).*

Appendix

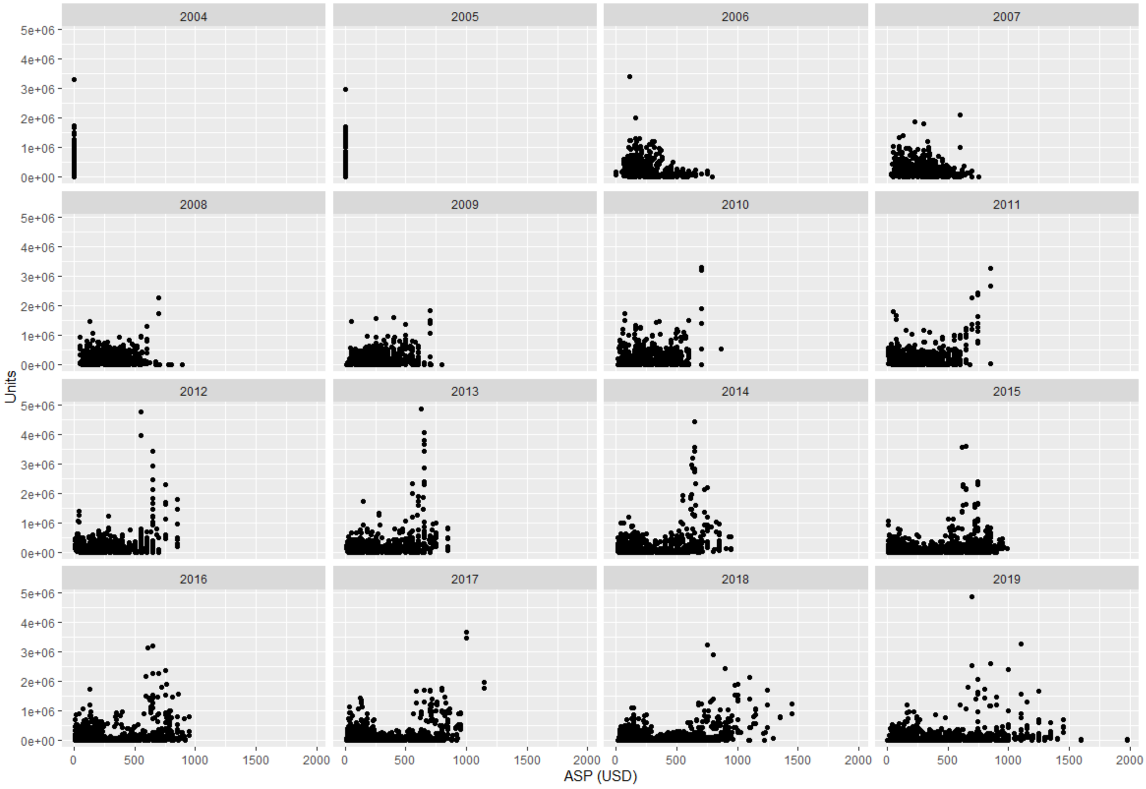


Figure 6.3: Partial Dependence Plot (PDP) of *ASP* for Western Europe

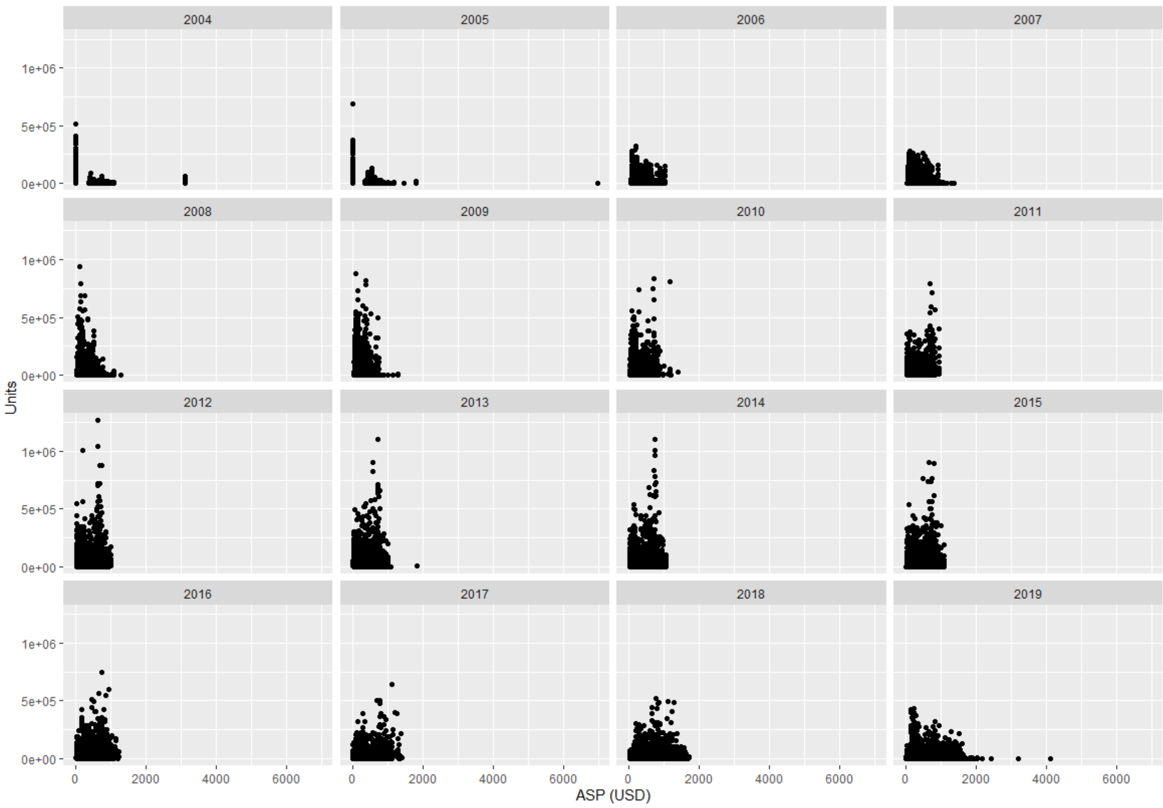


Figure 6.4: Partial Dependence Plot (PDP) of *ASP* for USA

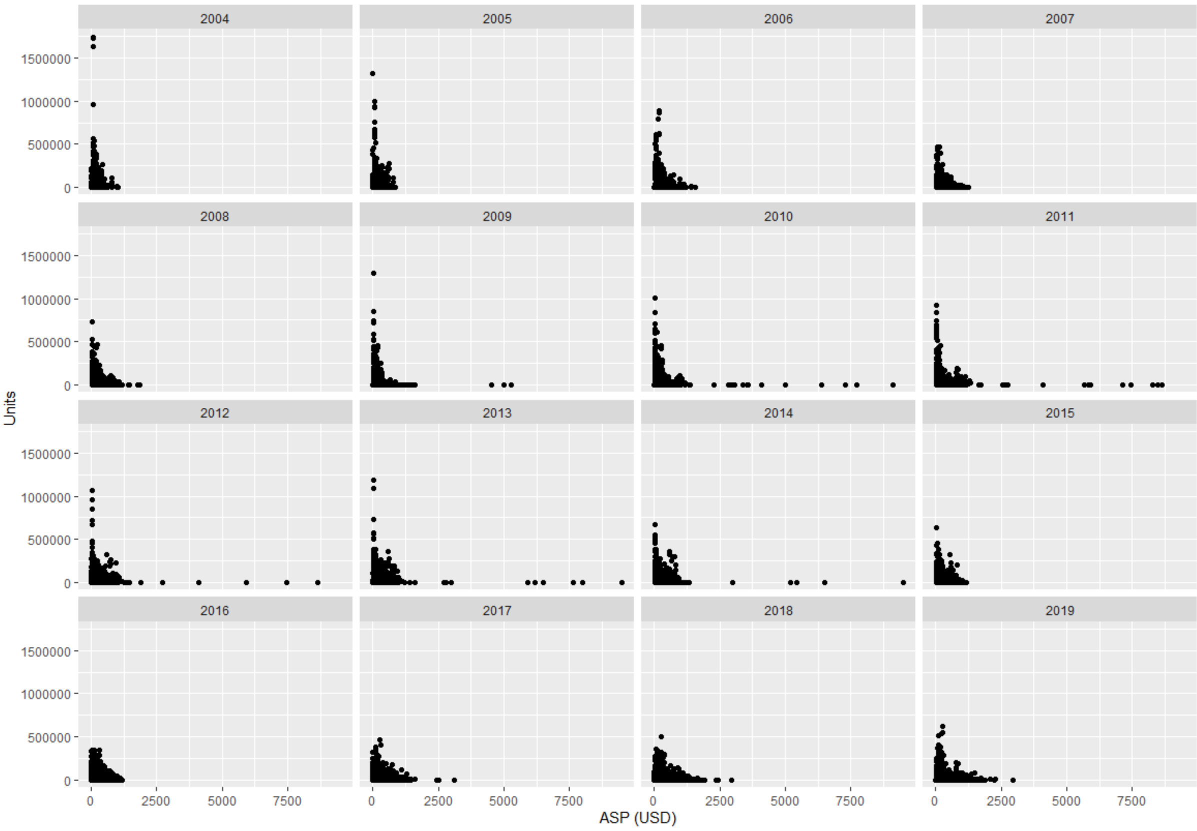


Figure 6.5: Partial Dependence Plot (PDP) of *ASP* for Central & Eastern Europe

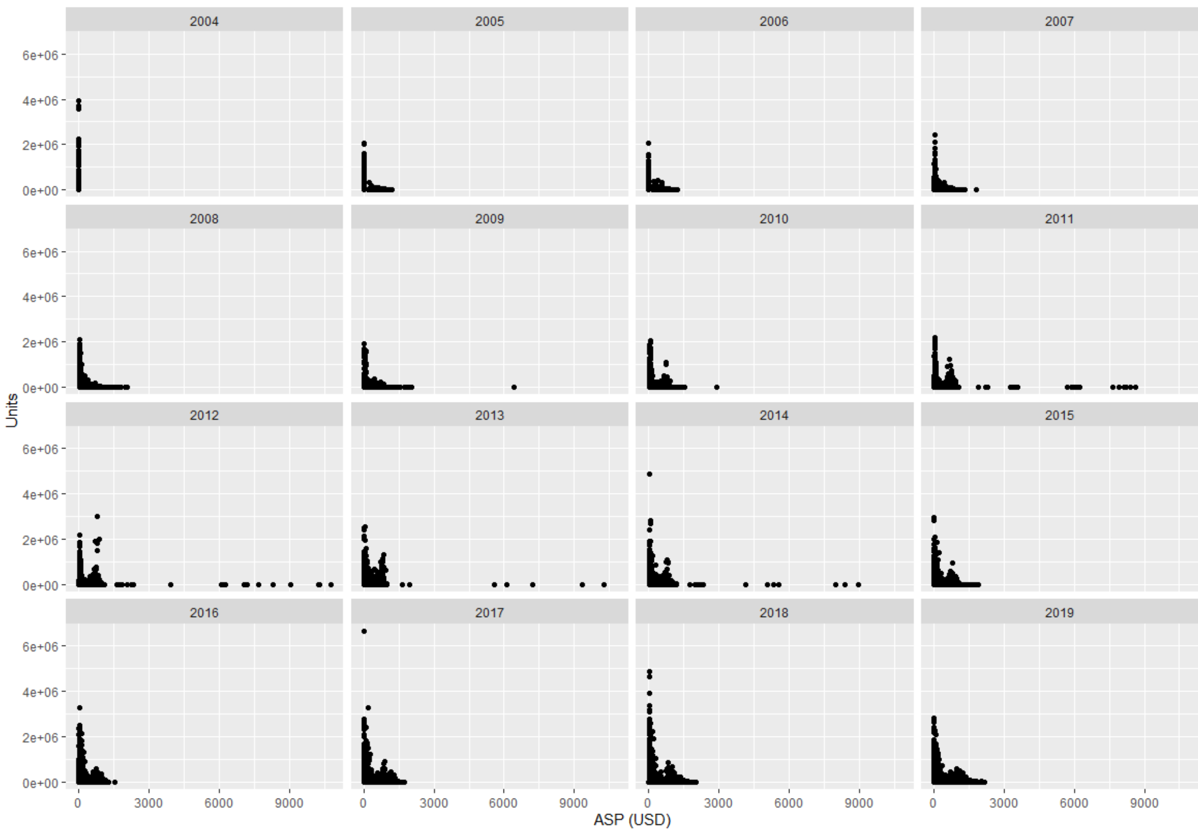


Figure 6.6: Partial Dependence Plot (PDP) of *ASP* for APeJC

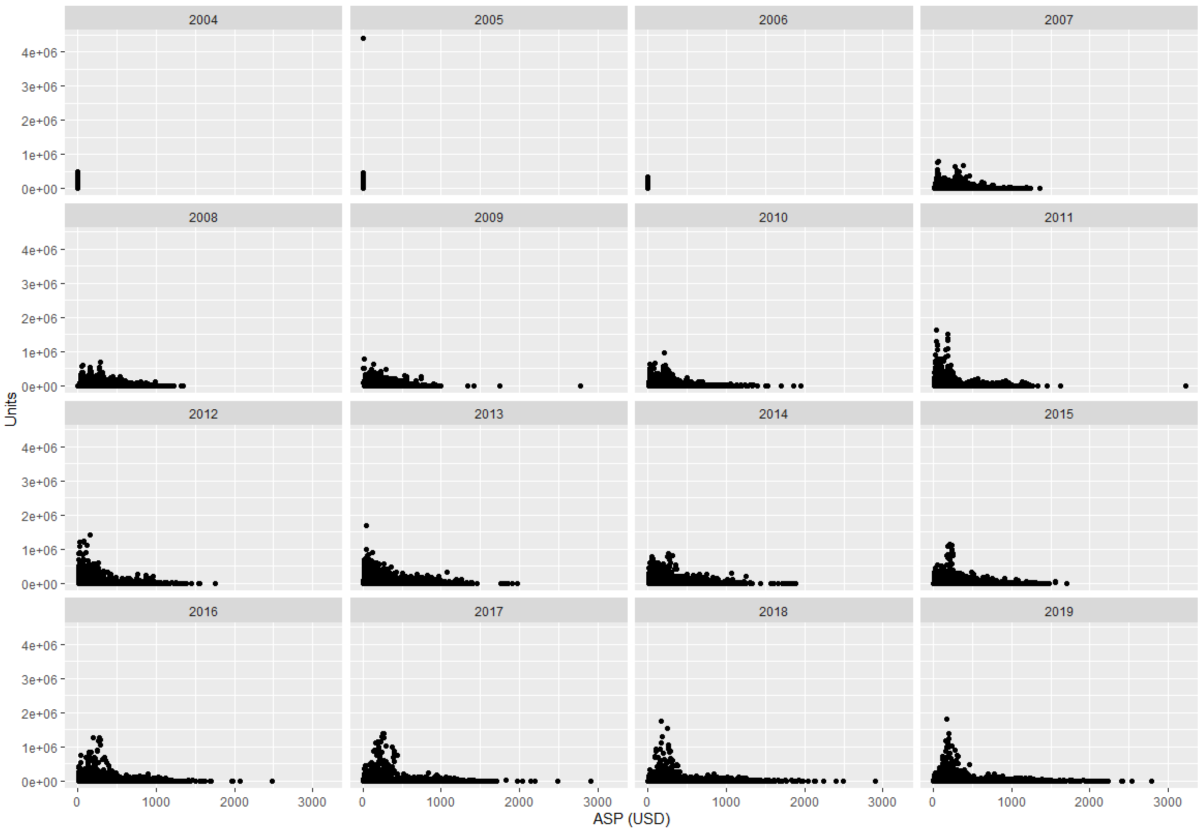


Figure 6.7: Partial Dependence Plot (PDP) of *ASP* for Middle East & Africa

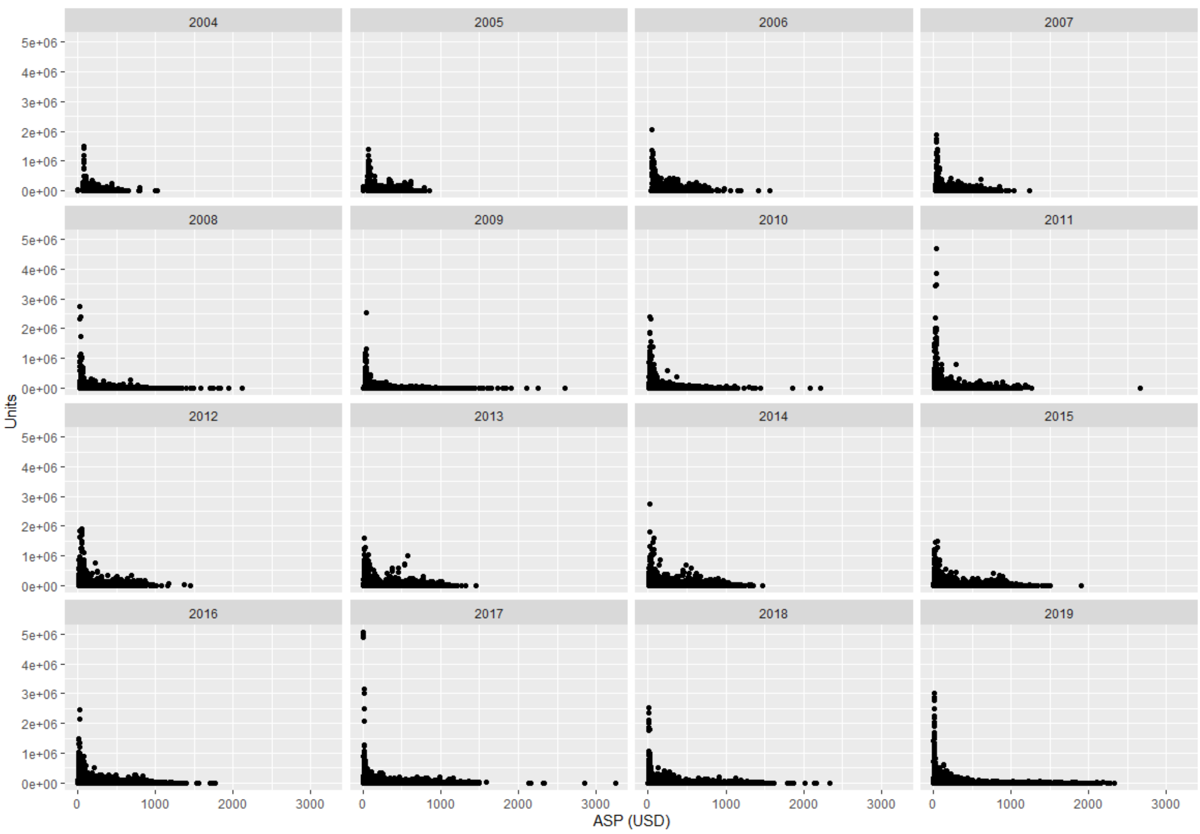


Figure 6.8: Partial Dependence Plot (PDP) of *ASP* for Latin America

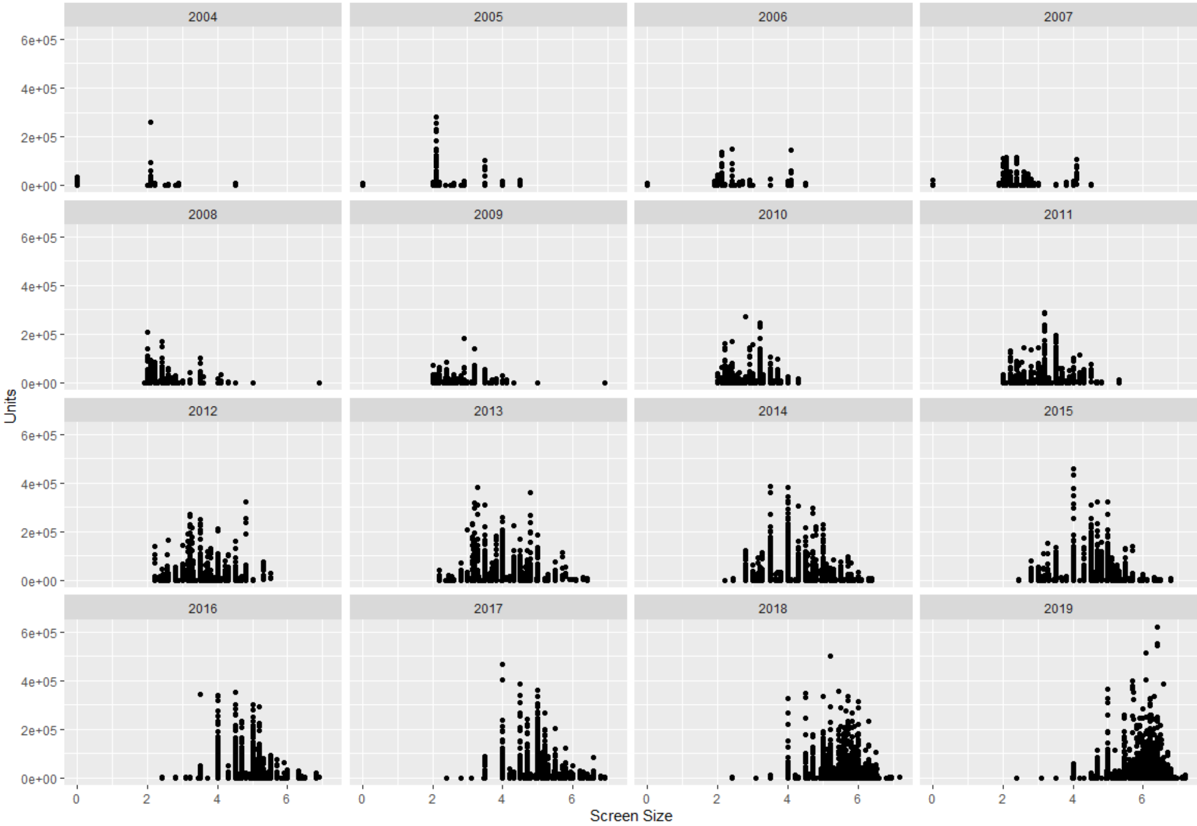


Figure 6.4A: Partial Dependence Plots (PDP) of *Screen Size* for Central & Eastern Europe

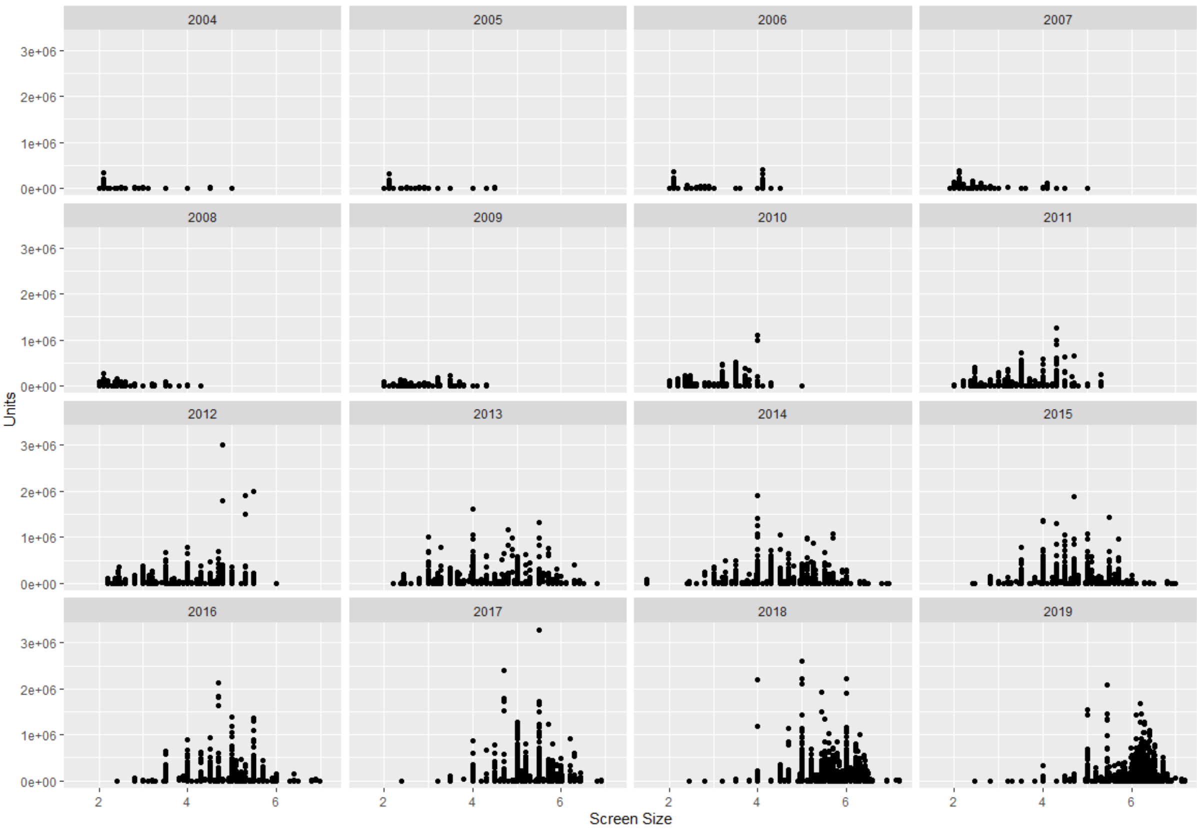


Figure 6.5A: Partial Dependence Plots (PDP) of *Screen Size* for APeJC

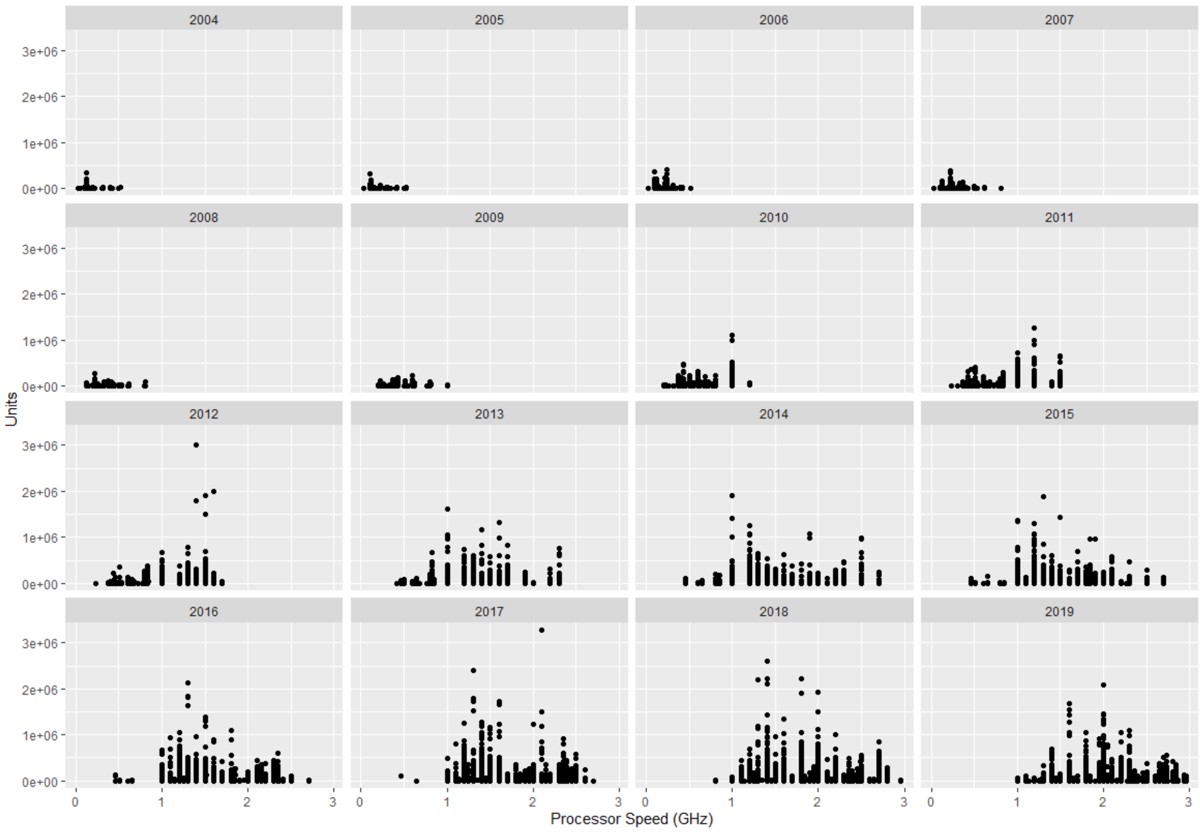


Figure 6.5B: Partial Dependence Plots (PDP) of *Processor Speed – Ghz* for APeJC

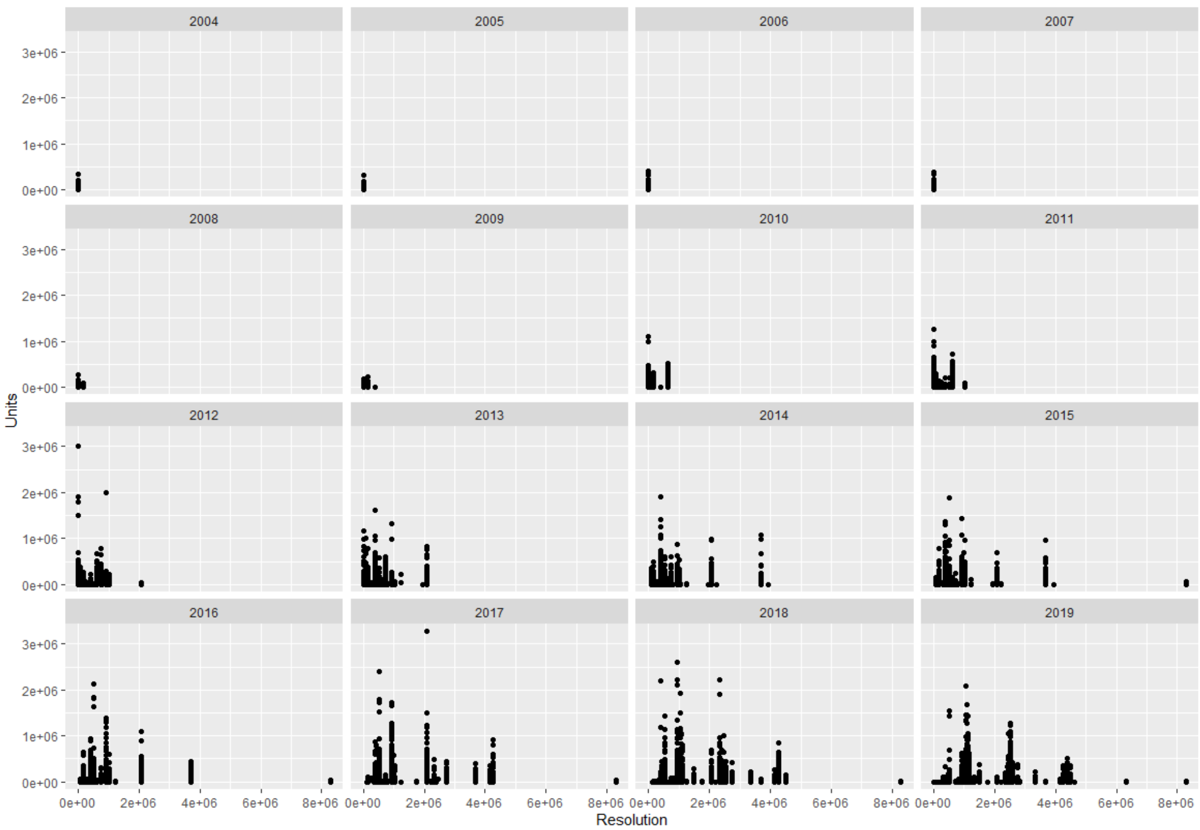


Figure 6.5C: Partial Dependence Plots (PDP) of *Resolution* for APeJC

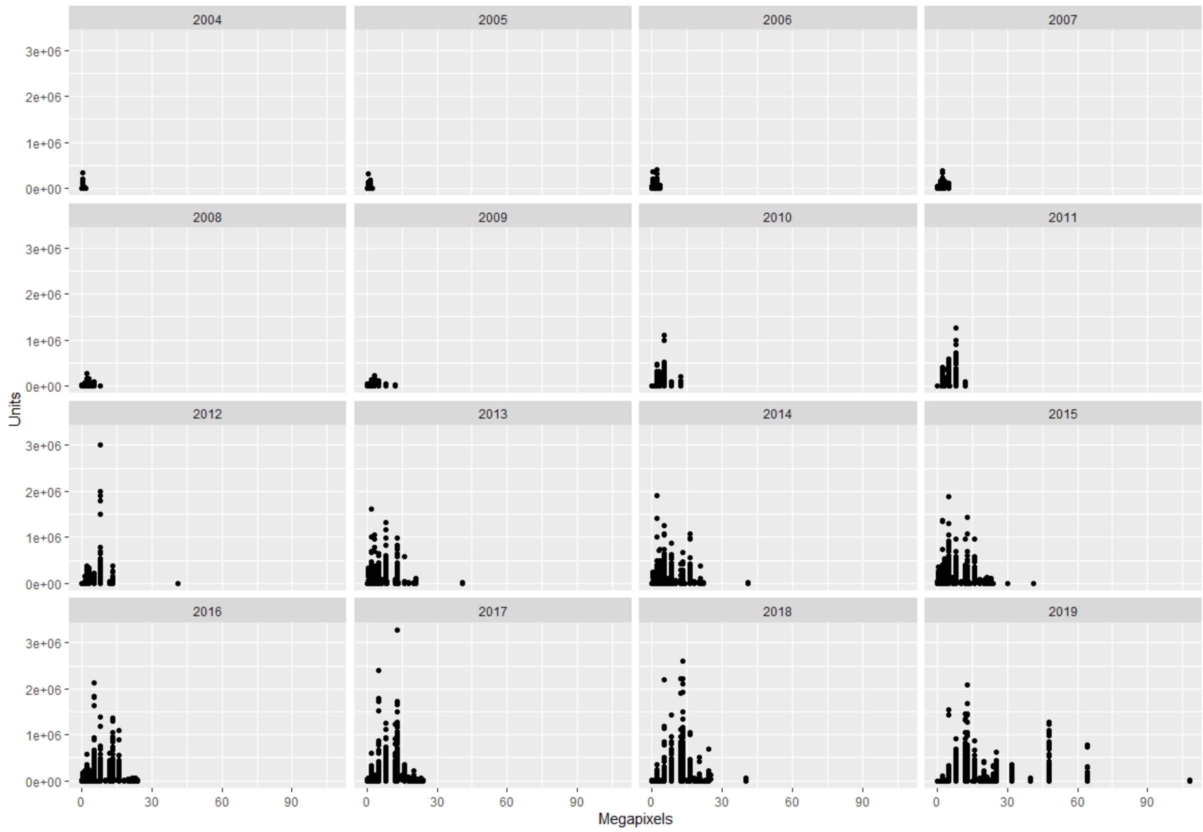


Figure 6.5E: Partial Dependence Plots (PDP) of *Megapixels* for APeJC

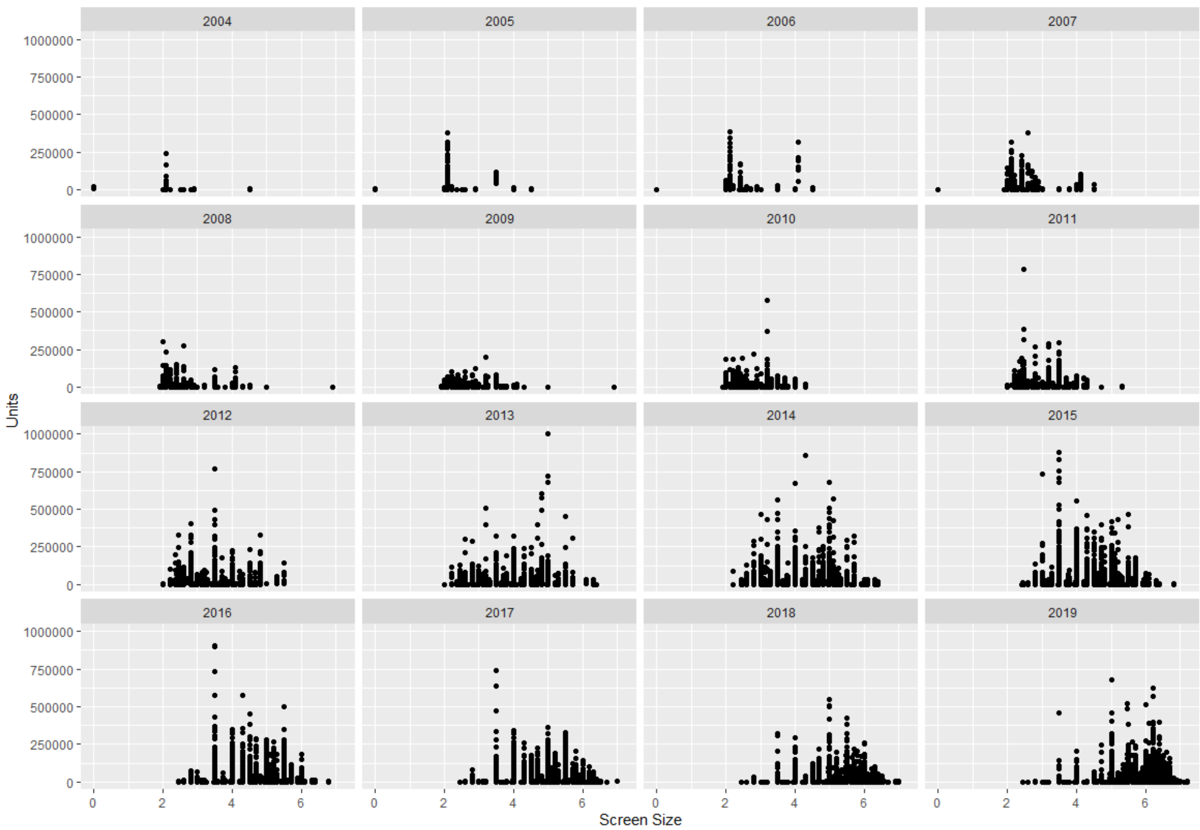


Figure 6.6B: Partial Dependence Plots (PDP) of *Screen Size* for Middle East & Africa

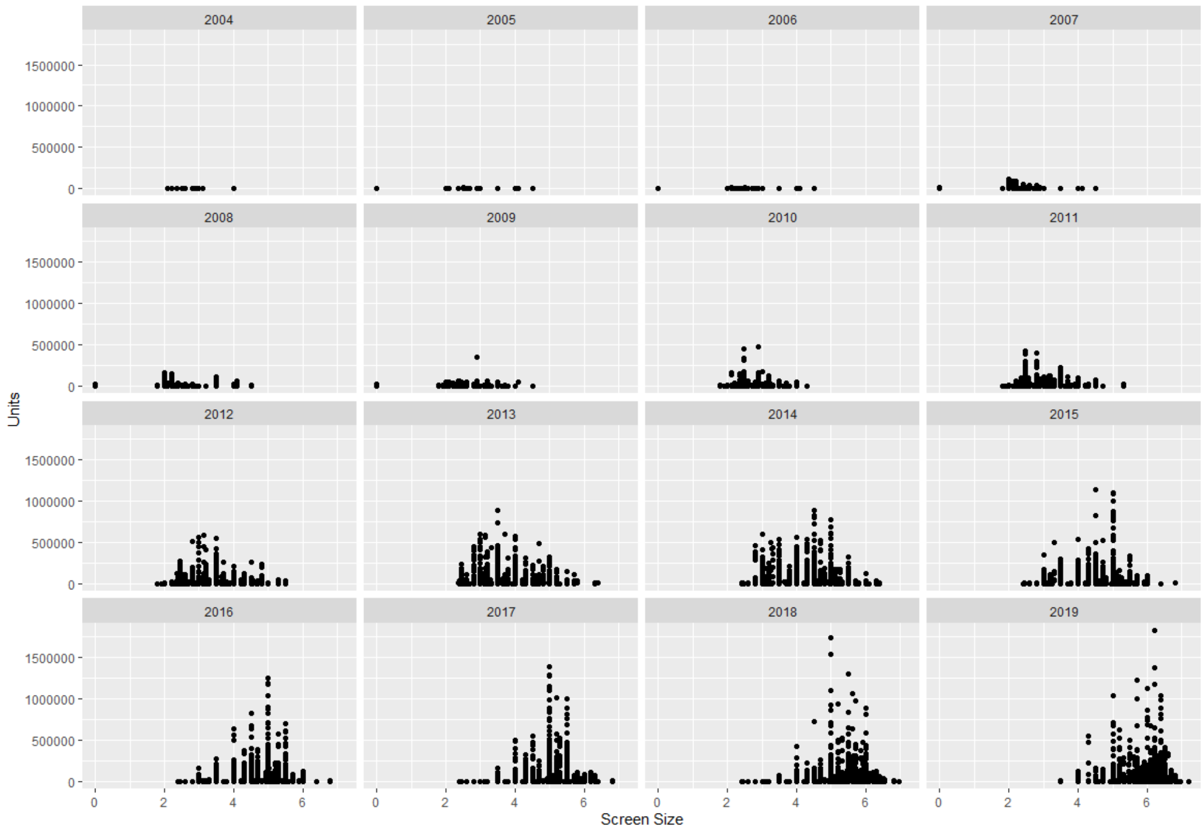


Figure 6.7A: Partial Dependence Plots (PDP) of *Screen Size* for Latin America

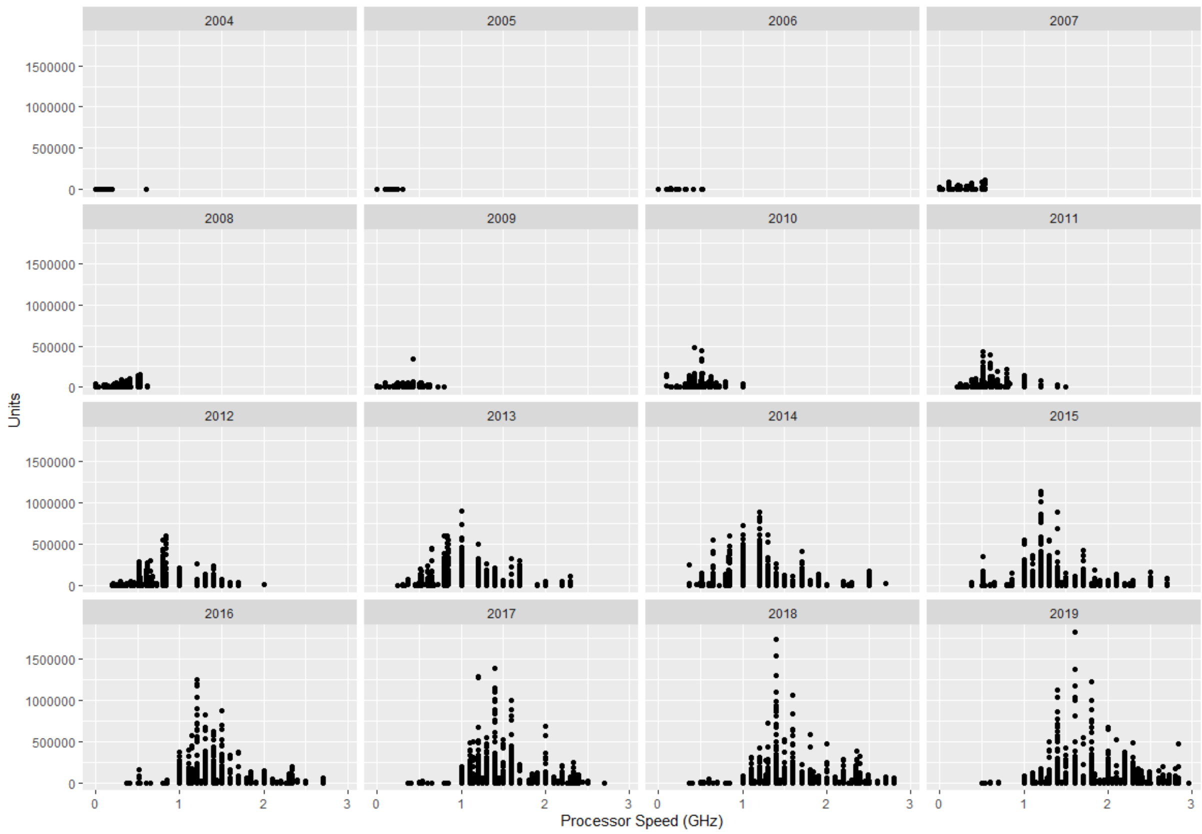


Figure 6.7B: Partial Dependence Plots (PDP) of *Processor Speed – Ghz* for Latin America

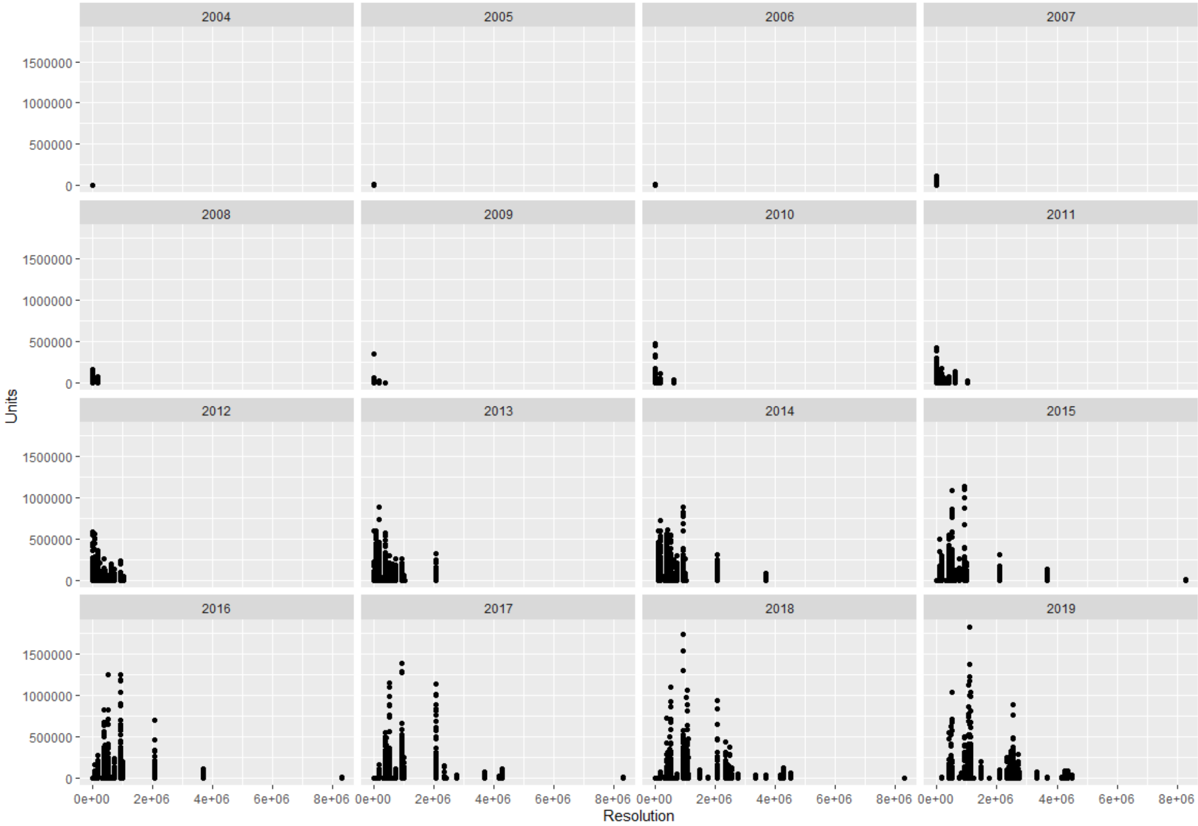


Figure 6.7C: Partial Dependence Plots (PDP) of *Resolution* for Latin America

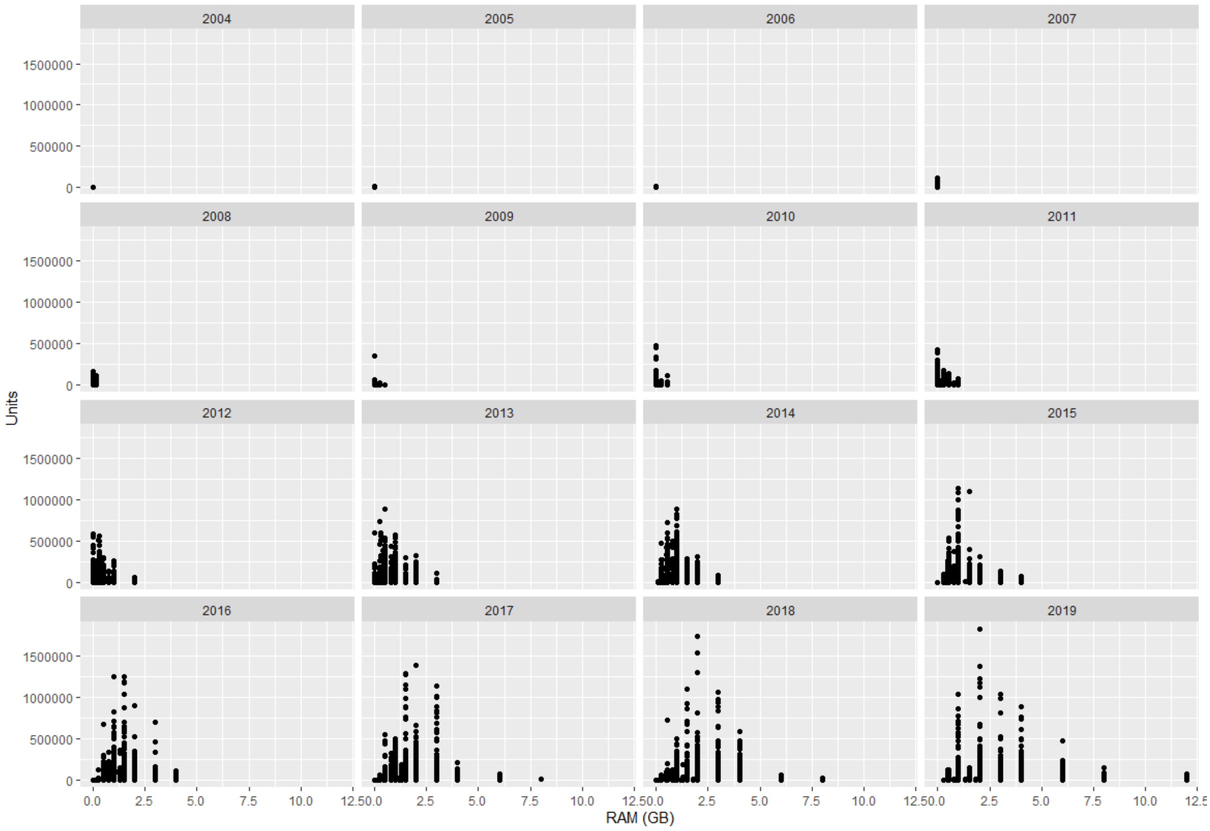


Figure 6.7D: Partial Dependence Plots (PDP) of *RAM - GB* for Latin America

Figure 7.1: Partial Dependence Plots (PDP) of *OS -iOS* for Western Europe