

Mobile Phones: Price Estimation

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Mission

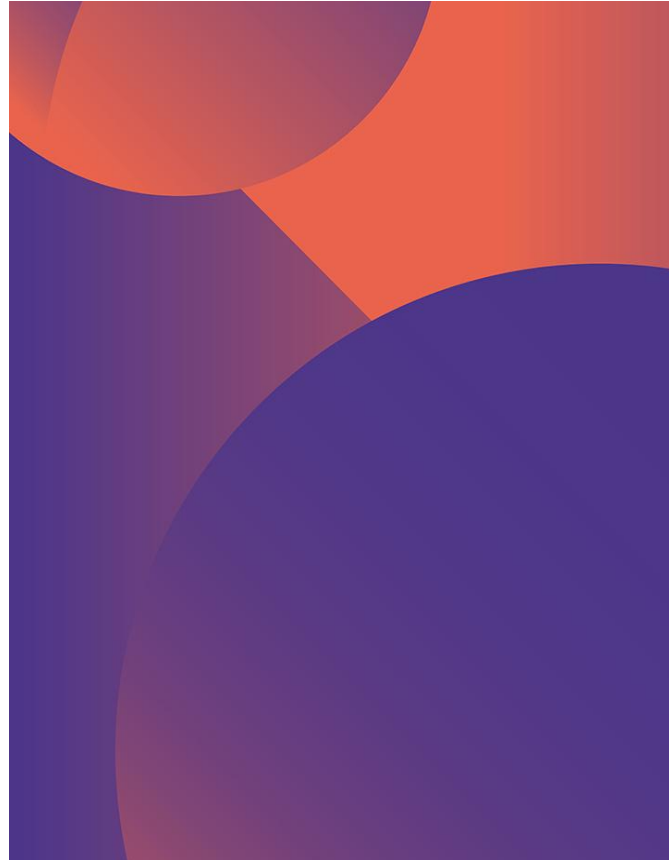
As a **mobile phone company**, price definition is extremely important step **before launching**

Goals of Machine Learning





- Predict the **price range** each phone should be sold
- Relationships between **features** (ex. battery, ram etc.) and **price range**



Company Strategy



Price Range (y)

	Values	Profitability
Very Low	0	
Low	1	
Medium	2	
High	3	

Mobile Phone Features (X)

Battery

Total energy a battery can store in one time

Ram

Random Access Memory (that means more RAM can let more apps run in the background without slowing your phone down)



Internal Memory

Internal Memory(storage space installed)

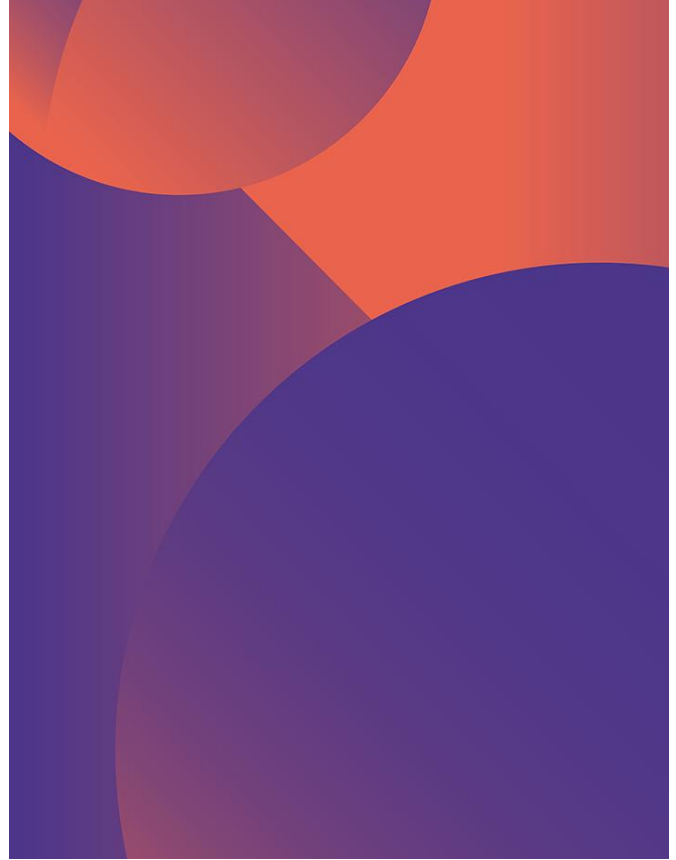
Clock Speed

Speed at which microprocessor executes instructions

If Prices Predicted are lower than Real Prices → company loses potential profits \$

	Actual Price	Predicted Price	Business Result (Profitability)
Predicted Prices = Actual Prices	Medium \$\$\$	Medium \$\$\$	
Predicted Prices > Actual Prices	Low \$	High \$\$\$\$	
Actual Prices > Predicted Prices	Medium \$\$\$	Low \$	

Project Timeline



ML Tasks



**Explore
Data**

**Define
Metric**

Based on the
company profit
strategy

$$\frac{y - \hat{y}}{\hat{y} + 1}$$

**Scale
Data**

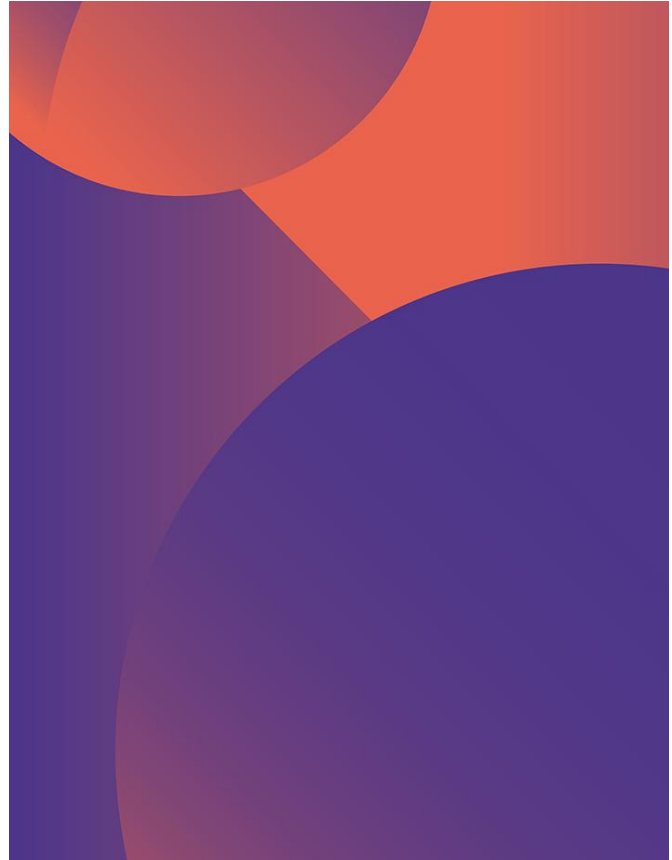
Models



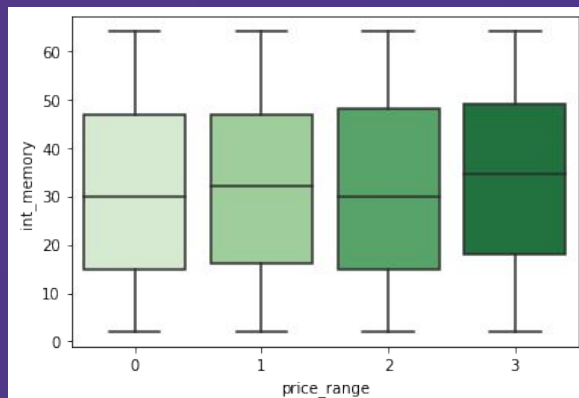
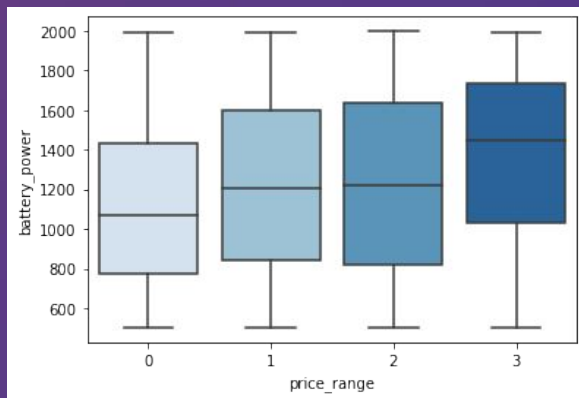
Summary



Exploratory Analysis

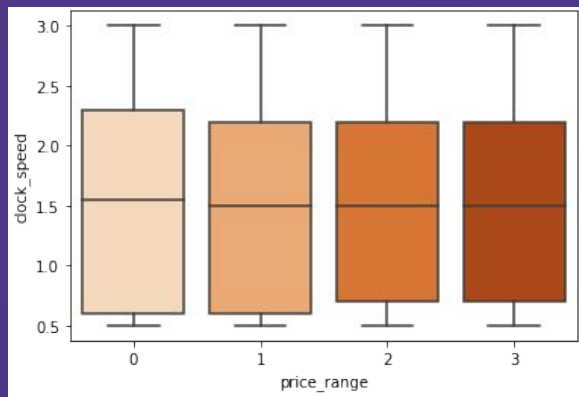
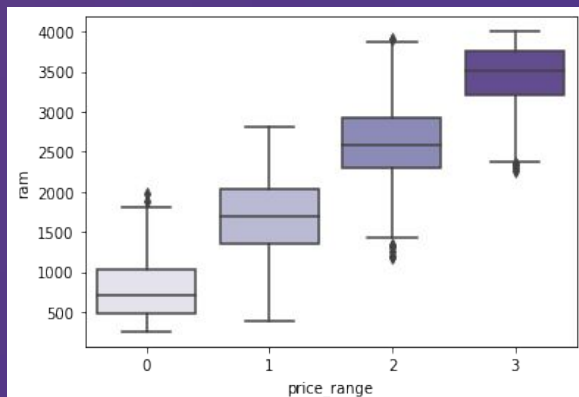


Relationship: Price and Features



Mobile phones with higher amount of **RAM memory** are clearly priced higher (**range=3**)

Similar pattern with **battery power** even if it looks that other features are more important in influencing the price range

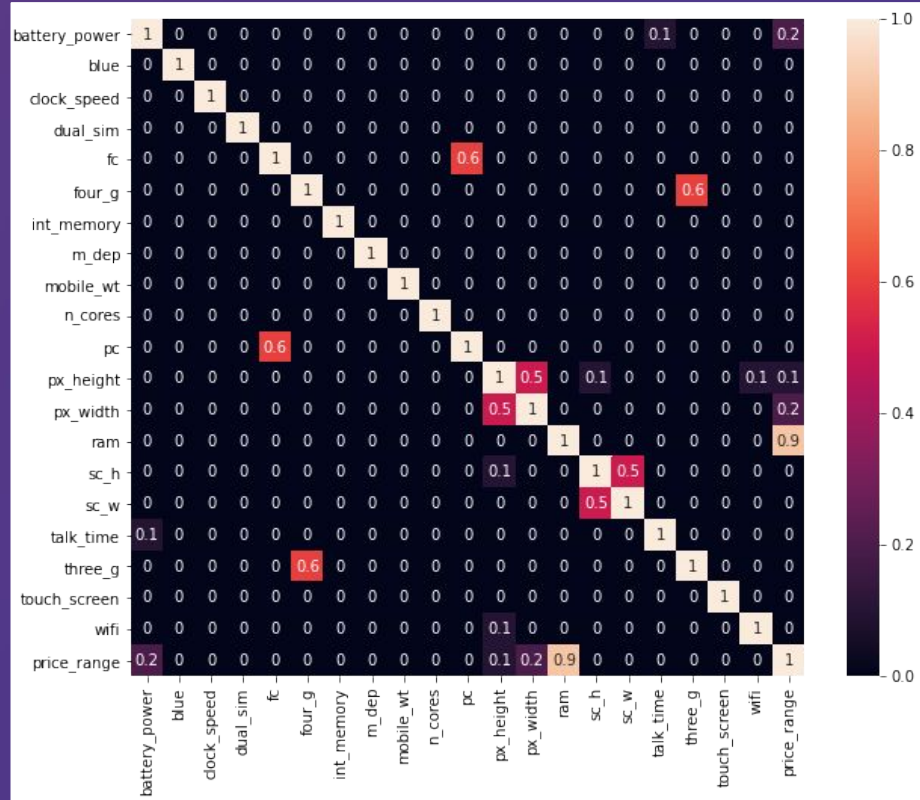


Clock speed and *internal memory* are not key factor to influence the price range

Statistics: data are not scaled

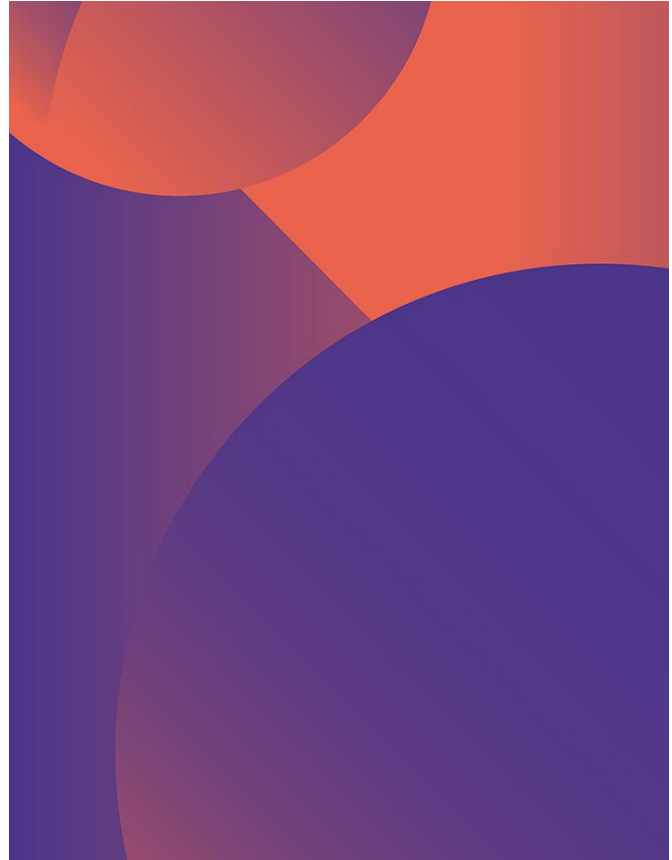
	count	mean	std	min	25%	50%	75%	max
battery_power	2000.0	1238.51850	439.418206	501.0	851.75	1226.0	1615.25	1998.0
blue	2000.0	0.49500	0.500100	0.0	0.00	0.0	1.00	1.0
clock_speed	2000.0	1.52225	0.816004	0.5	0.70	1.5	2.20	3.0
dual_sim	2000.0	0.50950	0.500035	0.0	0.00	1.0	1.00	1.0
fc	2000.0	4.30950	4.341444	0.0	1.00	3.0	7.00	19.0
four_g	2000.0	0.52150	0.499662	0.0	0.00	1.0	1.00	1.0
int_memory	2000.0	32.04650	18.145715	2.0	16.00	32.0	48.00	64.0
m_dep	2000.0	0.50175	0.288416	0.1	0.20	0.5	0.80	1.0
mobile_wt	2000.0	140.24900	35.399655	80.0	109.00	141.0	170.00	200.0
n_cores	2000.0	4.52050	2.287837	1.0	3.00	4.0	7.00	8.0
pc	2000.0	9.91650	6.064315	0.0	5.00	10.0	15.00	20.0
px_height	2000.0	645.10800	443.780811	0.0	282.75	564.0	947.25	1960.0
px_width	2000.0	1251.51550	432.199447	500.0	874.75	1247.0	1633.00	1998.0
ram	2000.0	2124.21300	1084.73204	256.0	1207.50	2146.5	3064.50	3998.0
sc_h	2000.0	12.30650	4.213245	5.0	9.00	12.0	16.00	19.0
sc_w	2000.0	5.76700	4.356398	0.0	2.00	5.0	9.00	18.0
talk_time	2000.0	11.01100	5.463955	2.0	6.00	11.0	16.00	20.0
three_g	2000.0	0.76150	0.426273	0.0	1.00	1.0	1.00	1.0
touch_screen	2000.0	0.50300	0.500116	0.0	0.00	1.0	1.00	1.0
wifi	2000.0	0.50700	0.500076	0.0	0.00	1.0	1.00	1.0
price_range	2000.0	1.50000	1.118314	0.0	0.75	1.5	2.25	3.0

Multicollinearity



Machine Learning

Supervised Machine Learning Model for **categorical** variable (price range)



Machine Learning



Question

Can we predict the price range of mobile phones?



Input

Mobile Phones Features (Ram, Battery etc.)



Output

Price Range (Very Low, Low, Medium, High)

Machine Learning Models

Models Developed: Logistic Regressions, AdaBoost, K-Nearest Neighbors, Support Vector Machine, Gaussian Naive Bayes, Decision Tree, Random Forest, CatBoost

Evaluation: the most accurate models in predicting the prices are: **Catboost** and **SVM**

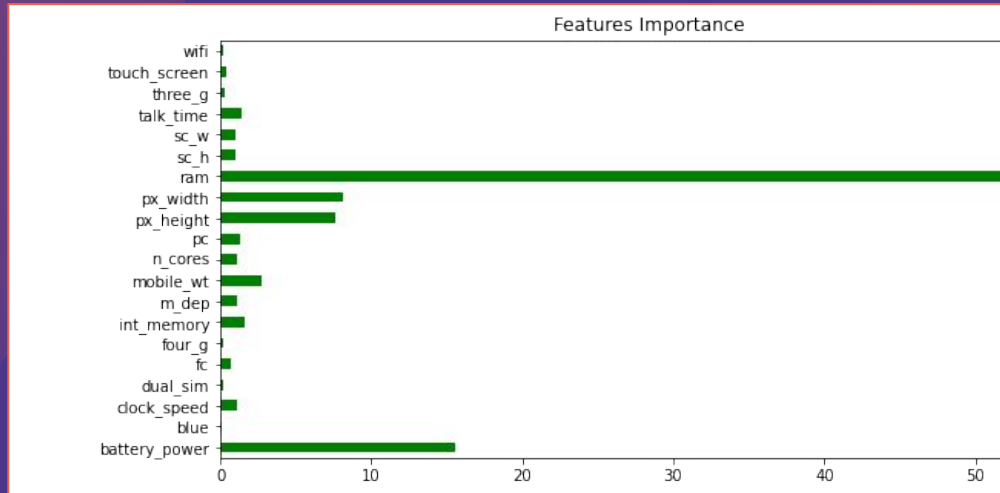
1. **SVM:** It has the lowest value of the score of the the *New Metric*, so it is the best (the metric was created based on the company profitability strategy → where this assumption rules: **actual price (y) <= predicted price \hat{y}**)
2. **CatBoost:** it has the second **highest scores** in **all** the standard evaluation metrics (excluding new metric),

	Accuracy	Precision	Recall	F1	New Metric
LR	0.250375	0.250375	0.250375	0.250375	108.345827
KNN	0.250375	0.250375	0.250375	0.250375	108.345827
Ada	0.644678	0.644678	0.644678	0.644678	20.977011
NB	0.806597	0.806597	0.806597	0.806597	8.870565
DT	0.823088	0.823088	0.823088	0.823088	8.42079
RF	0.881559	0.881559	0.881559	0.881559	5.134933
Cat	0.946027	0.946027	0.946027	0.946027	2.373813
SVM	0.958021	0.958021	0.958021	0.958021	1.686657

$$\frac{y - \hat{y}}{\hat{y} + 1}$$

Features Importance:

- **SVM:** The feature importance of a **nonlinear SVMs** can not be found out. The reason being is that, when the SVM is non-linear the dataset is mapped into a space of higher dimension
- **CatBoost:** the most relatively important feature for the prediction is **RAM** memory, followed by the **battery power** of the mobile phone.
→ NB: this match with the observation done during the **exploratory analysis**



A woman with long dark hair, wearing a light-colored blazer, is leaning over a man with a beard and short hair, who is wearing a checkered shirt. They are both smiling and looking at a laptop screen. The man is sitting at a desk, and the woman is standing behind him. In the background, there are other people working at desks, and large windows showing a city view. The image has a warm, orange-red tint.

Q&A