A close-up photograph of a person's hands holding a black smartphone. The person is wearing a light blue denim jacket over a dark shirt. The background is blurred, showing what appears to be a city street.

An Analysis of cell Phone Features
and Their Relationship With Pricing

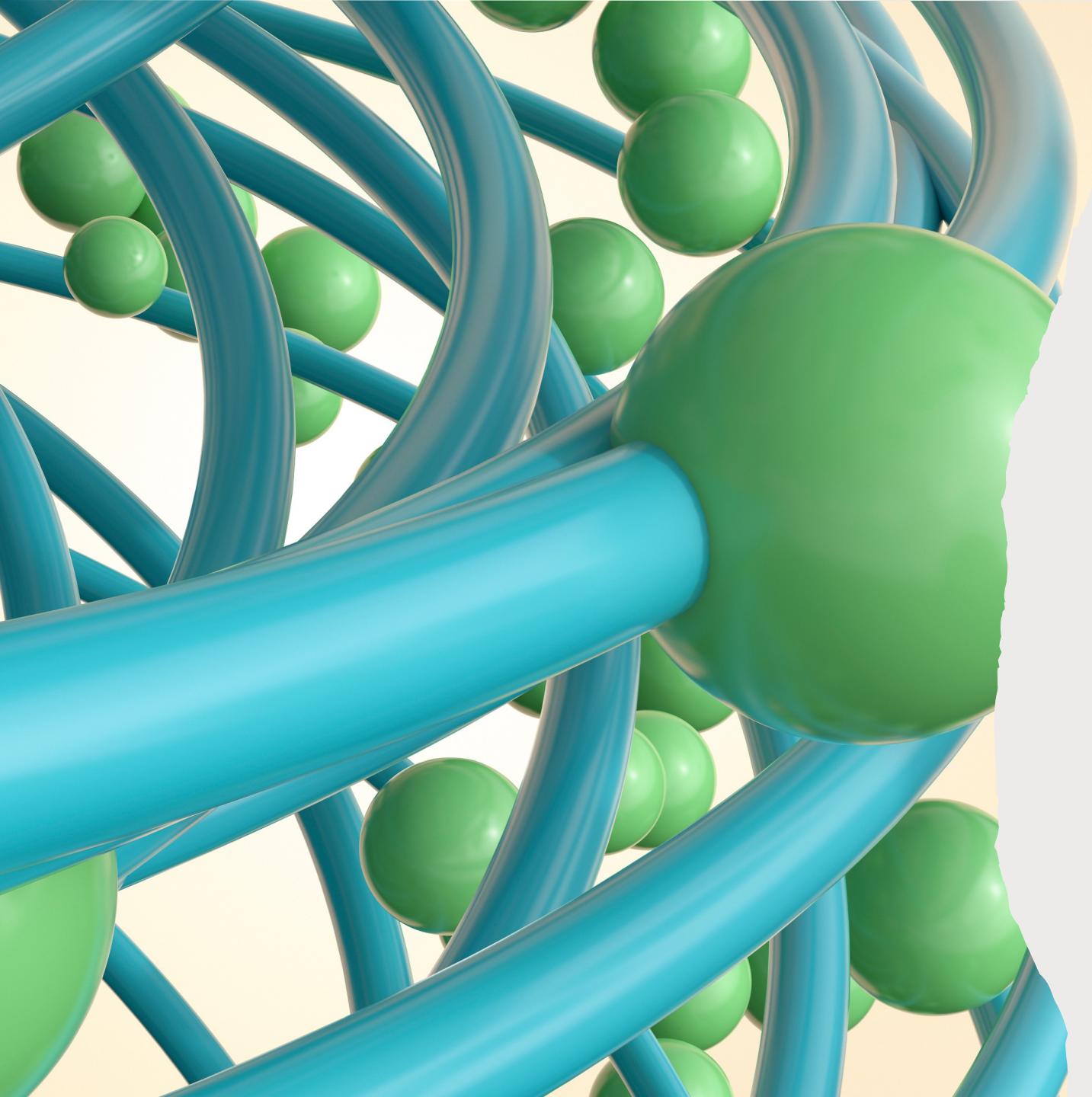
New Phone. Who's This?

Why Study Cell Phone Features?

- Used by a Majority of People
- Technological Advances
- Need to Find Best Value for Phone
 - Consumer Purchasing Power
 - Cost to Manufacturers
- Ability to Change Lives
 - Lil Nas X and Tiktok



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A close-up, abstract 3D rendering of a complex network of thick, translucent blue tubes and green spheres. The tubes are intertwined in various directions, creating a sense of depth and complexity. The spheres are scattered throughout the scene, some partially hidden behind the tubes. The lighting is soft, highlighting the rounded shapes of the spheres and the curved surfaces of the tubes.

Related Work

- Nivitus²
 - Pandemic Phone Pricing
 - Minimal Attributes
 - No Error Testing
- Al-Shawwa, Abu-Naser and Nasser³
 - Neural Network
 - Difficult Interpretability
 - We Want the Opposite
- Asim and Khan⁴
 - Naïve Bayes and Decision Tree Classifiers
 - Inflation Ignored

Proposed Work: Tools and Data Attribute

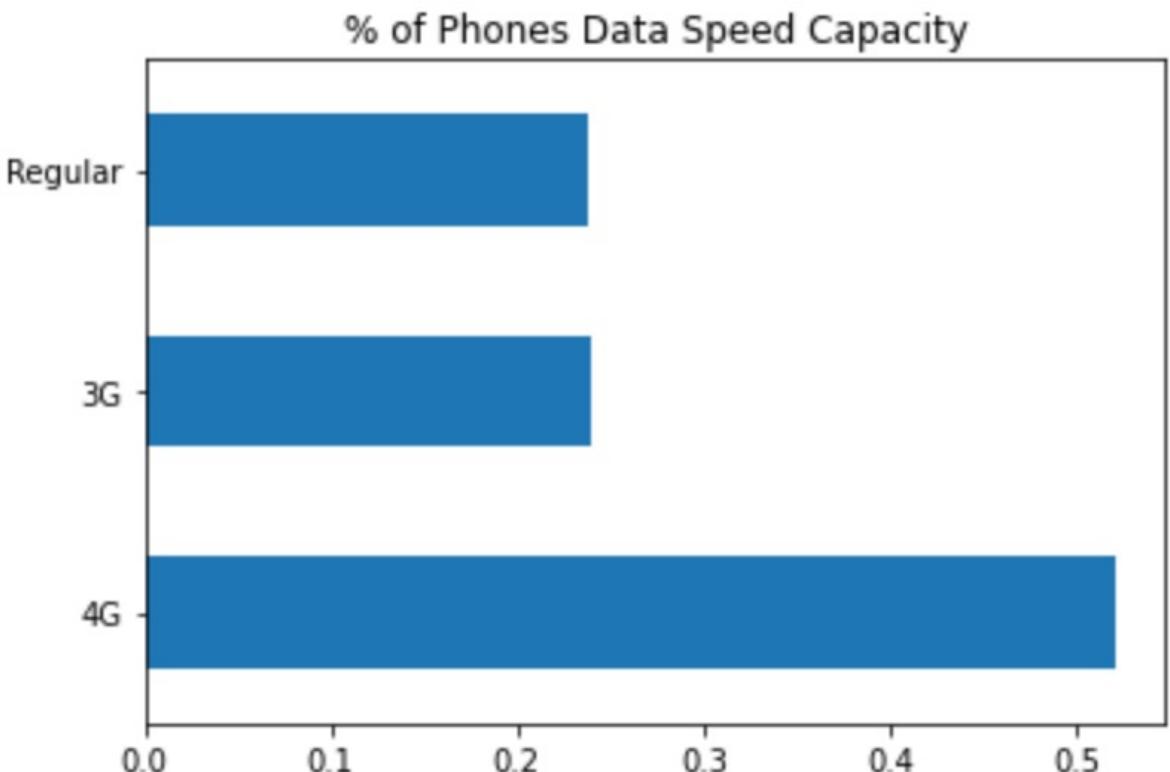
- Cell Phone Hardware
 - Battery Power
 - Blue
 - Clock Speed
 - Dual Sim
 - Front Camera
 - 4G
 - Internal Memory
 - Mobile Depth
 - Mobile Weight
 - Number of Cores
 - Primary Camera
 - Pixel height
 - Pixel Width
 - RAM
 - Screen Height
 - Screen Width
 - Talk Time
 - 3G
 - Touch Screen
 - Wifi
 - Price Range (Response)



- Analysis Using Python
- Data Set
 - Absihik Sharma
 - Kaggle

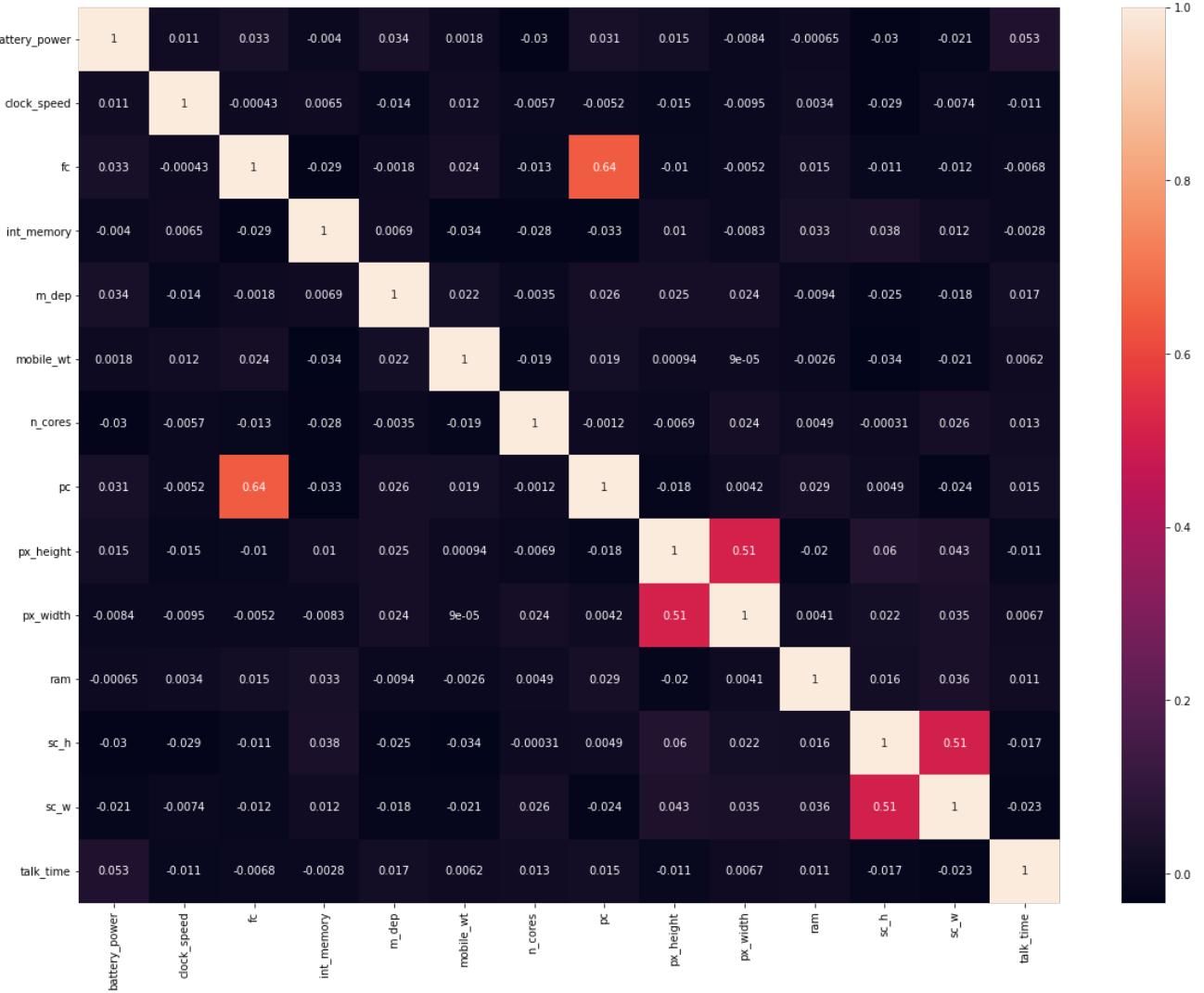
Data Understanding

- Overview
 - 2000 Observations
 - 14 Continuous and 7 Categorical Variables
 - 7 Binary Categories
- Response Variable
 - Price Range
 - Low
 - Below Average
 - Above Average
 - high
 - 500 Each
- Data Speed Capacity (Graph on Right)
 - Uneven Levels
- Split 70/10/20 for train, validation and tests set
- Metric: Accuracy
 - Want to be as accurate as possible
- Warehousing
 - Two csv files



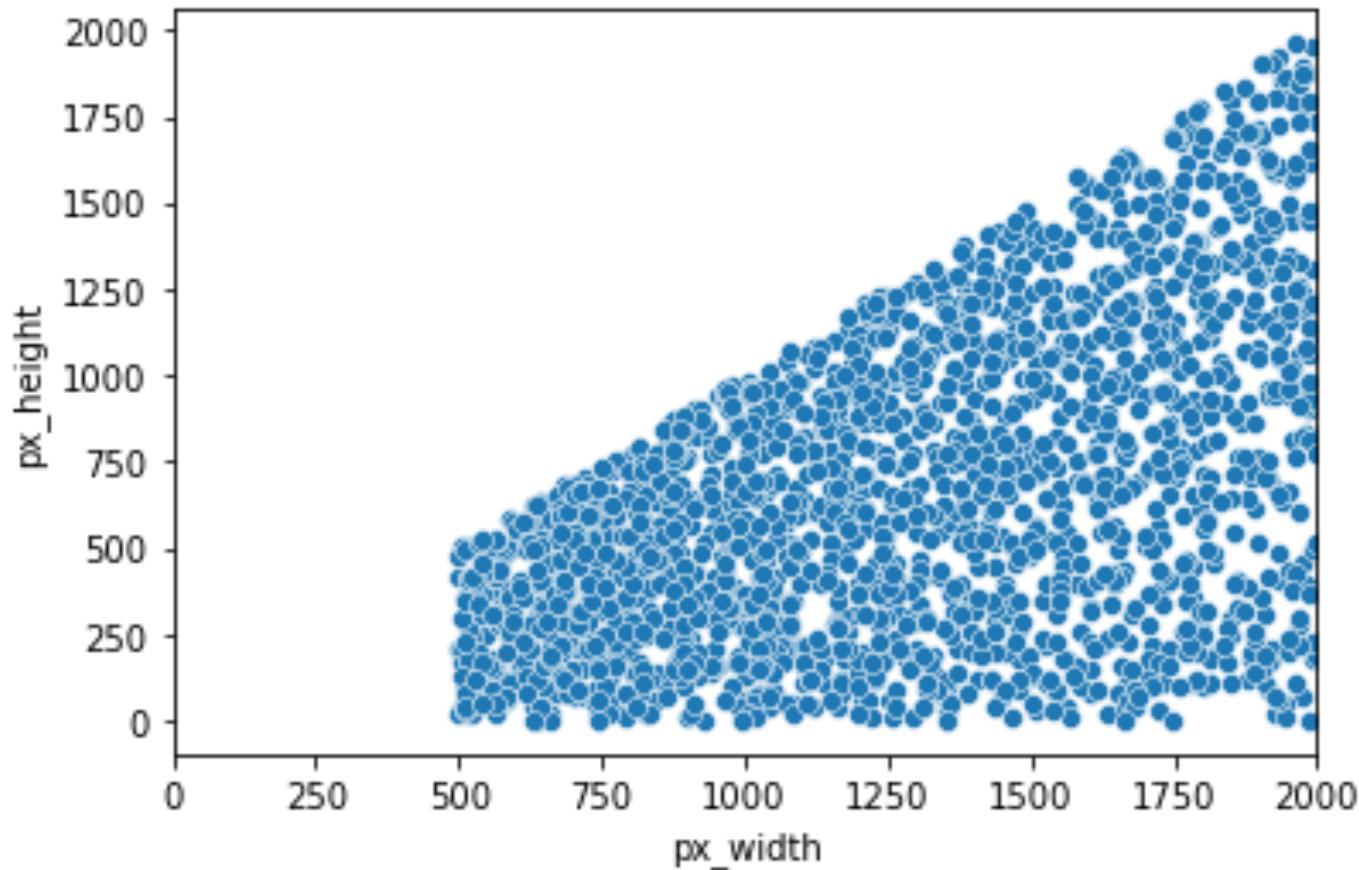
Continuous Correlation

- Front Camera and Primary Camera Highly Correlated
 - Makes sense for both Cameras to be Similar Quality
- Pixel Width and Pixel Height
 - Expected Correlation



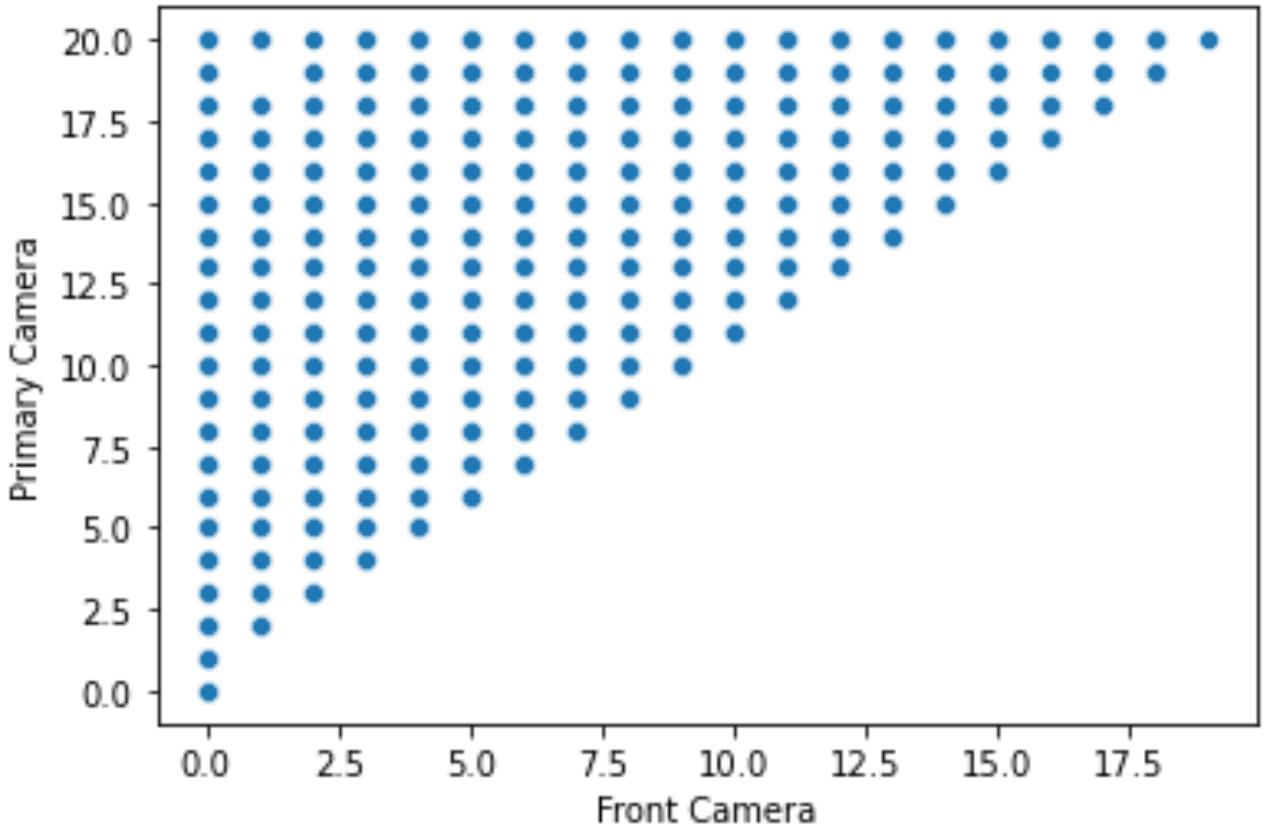
Pixel Height and Pixel Width

- Minimal Pixel Width is 500
- Height \geq Width
- Usual Pixel Resolution
 - 1280 x 1024
 - 1920 x 1080
 - 2560 x 1440



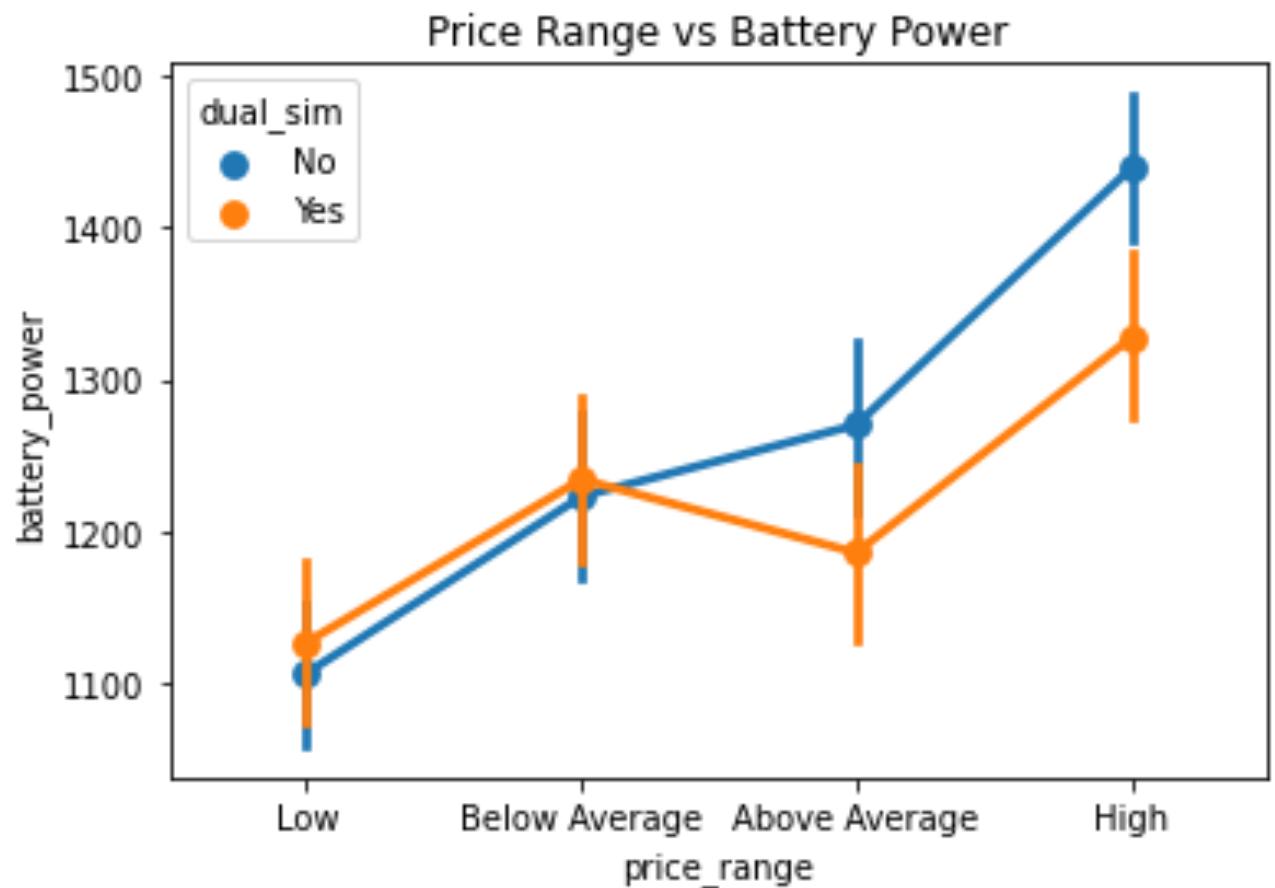
Price Range vs Battery Power

- Primary Camera \geq Front Camera
- Confirms hypothesis Primary Camera $>$ Front Camera



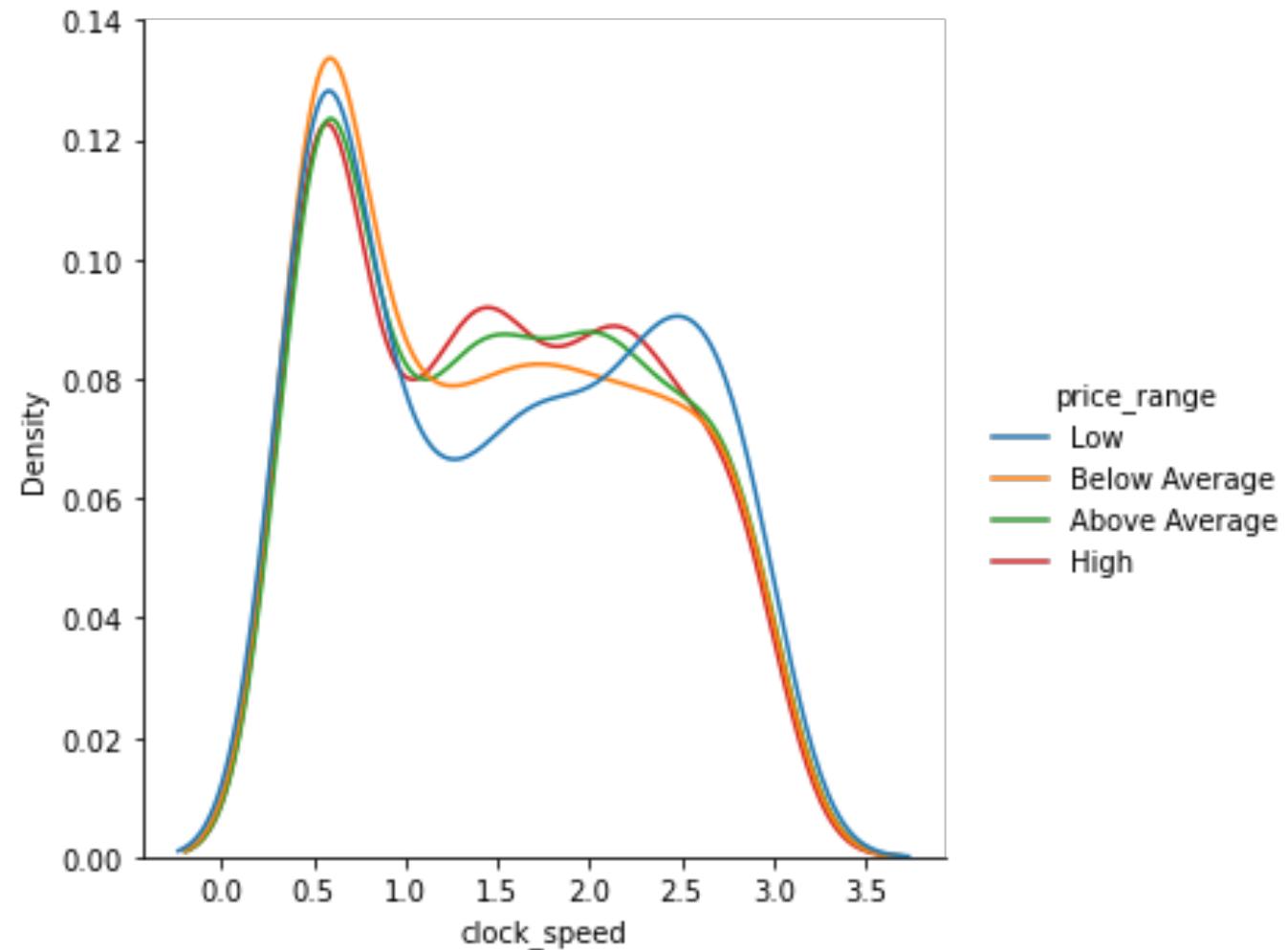
Primary Camera and Face Camera

- Important, regardless of location
- Dual Sim Cards less Prevalent in Higher Priced Devices
- Smart Phones Store Data without Sims
- Higher Prices = More Battery Power
- Lower Prices = Less Battery Power



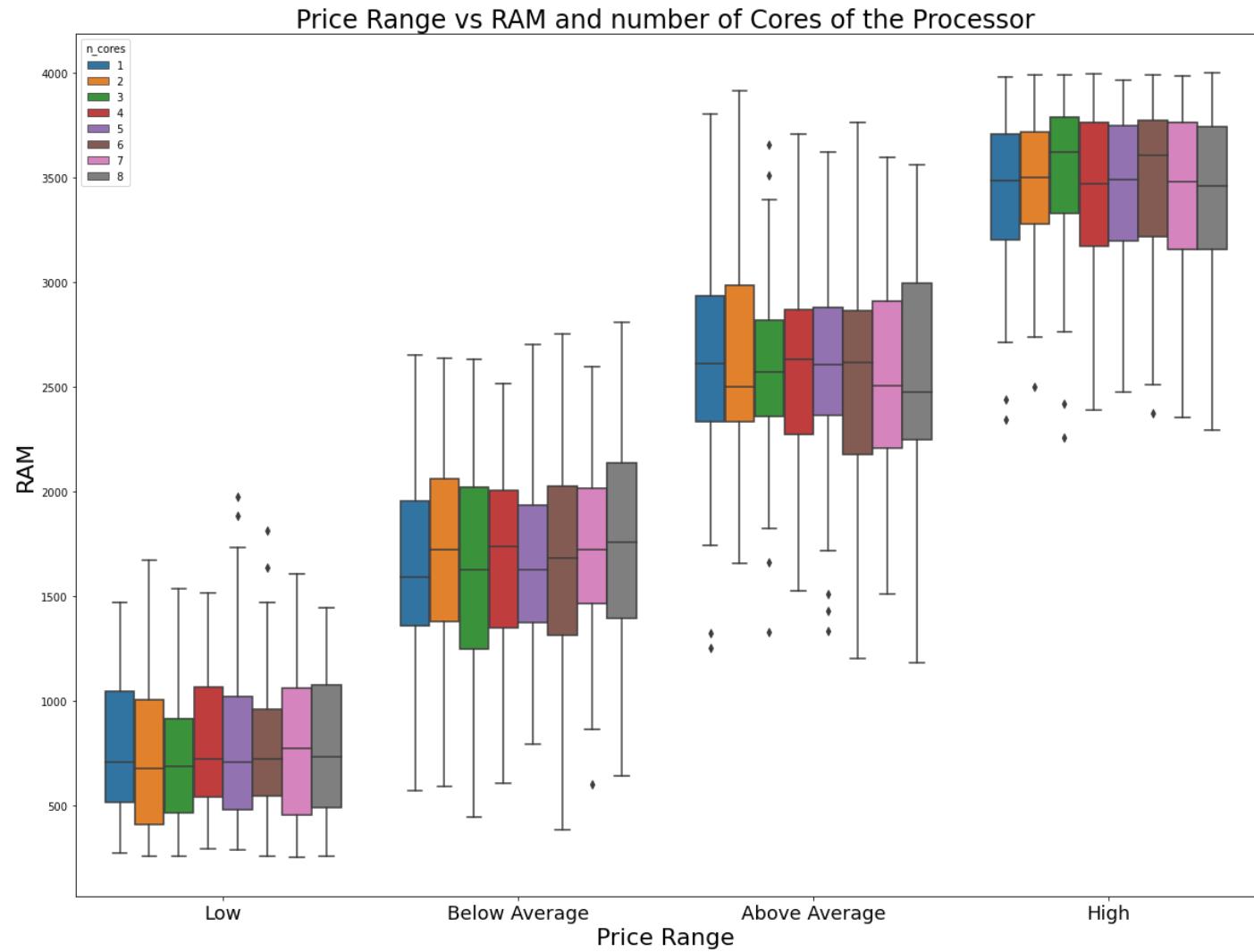
Price Range and Clock Speed

- Hypothesis: Higher Priced Phones Have Lower Clock Speed
- Low Prices = slower speed
- Other Prices Are Similar Speeds



Price Range and Clock Speed

- Hypothesis: Higher RAM = More Processors and Expensive Phone
- Visualization Shows No Relationship Between RAM and Processor Count
- The higher the prices, the more RAM



Price Range and Touch Screen Capability

- Hypothesis: Touch Screen = Expensive Phone
- Hypothesis Test
 - H_0 : Price Range and Touch Screen Capability are independent
 - H_1 : Price Range and Touch Screen Capability are not independent.
- P-Value: 0.27
 - Independent

touch_screen	No	Yes
price_range		
Above Average	265	235
Below Average	239	261
High	252	248
Low	238	262

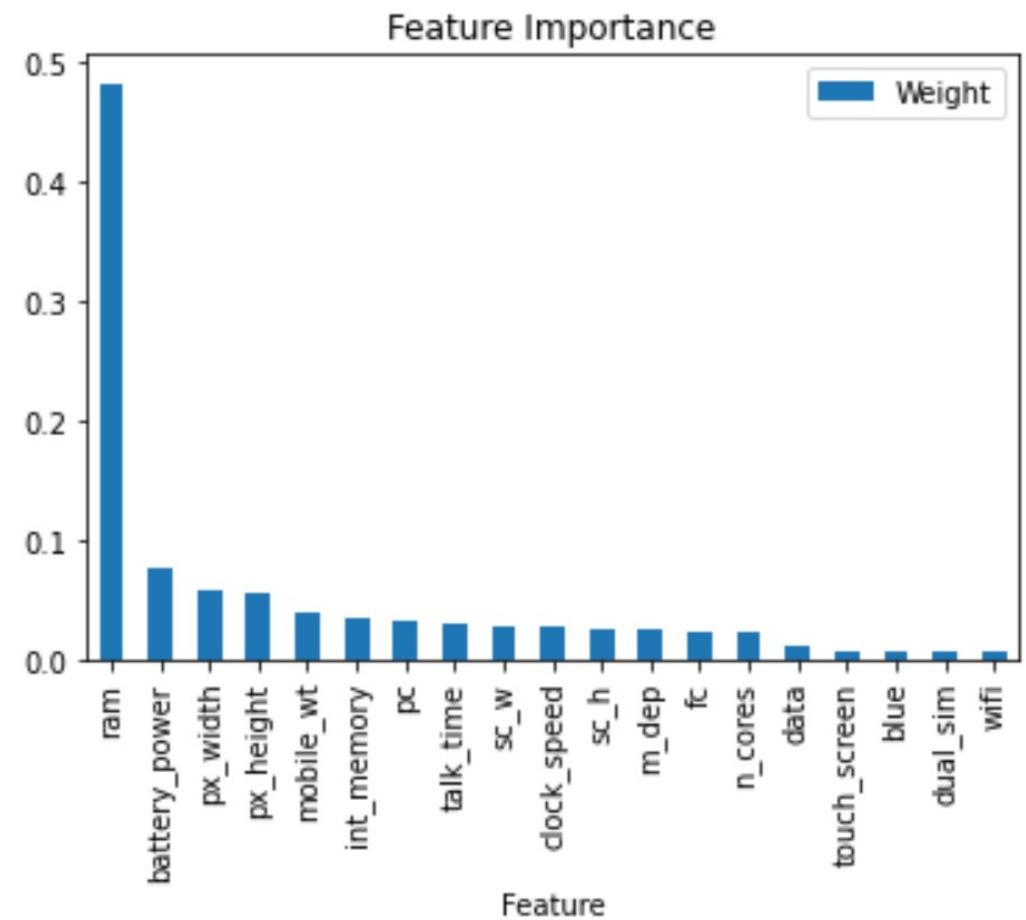
Model Training and Candidates

- Experimental Method
 - Training Set: 70%
 - Validation Set: 10%
 - Test Set: 20%
- Accuracy: Best Measurement
 - Expensive Phone Deters Consumer and Manufacturer
 - Inexpensive Phone loses profits
- Model Chosen: Random Forest
 - Best Interpretability
 - High Accuracy

Model	Accuracy (%)
Support Vector Machine	94.56
K Nearest Neighbors	91.56
Random Forest	86.69
Decision Tree	81.69
Multinomial Logistic Regression	71.00

Feature Importance

- Random Access Memory (RAM)
 - Most Important
- Battery life and Pixel Dimensions contribute a lot
 - Less charging
 - More Mobility
- Dropped Features from Model
 - Data Speed
 - Touch Screen Capability
 - WIFI
 - Bluetooth
 - Dual-Sim



Validation Set Test

- Accuracy: 89%
- Hyperparameter Tuning:
GridSearchCV
 - bootstrap: True
 - criterion: Entropy
 - max_Depth: 10
 - min_samples_split: 5
 - n_estimators: 500
- Precision and Recall Improvement

Before Hyperparameter Tuning

	precision	recall	f1-score	support
Low	0.88	0.93	0.91	88
Below Avg	0.88	0.86	0.87	108
Above Avg	0.83	0.88	0.85	97
High	0.95	0.88	0.91	107
accuracy			0.89	400
macro avg	0.89	0.89	0.89	400
weighted avg	0.89	0.89	0.89	400

After Hyper Parameter Tuning

	precision	recall	f1-score	support
Low	0.88	0.94	0.91	88
Below Avg	0.88	0.86	0.87	108
Above Avg	0.86	0.86	0.86	97
High	0.94	0.92	0.93	107
accuracy			0.89	400
macro avg	0.89	0.89	0.89	400
weighted avg	0.89	0.89	0.89	400

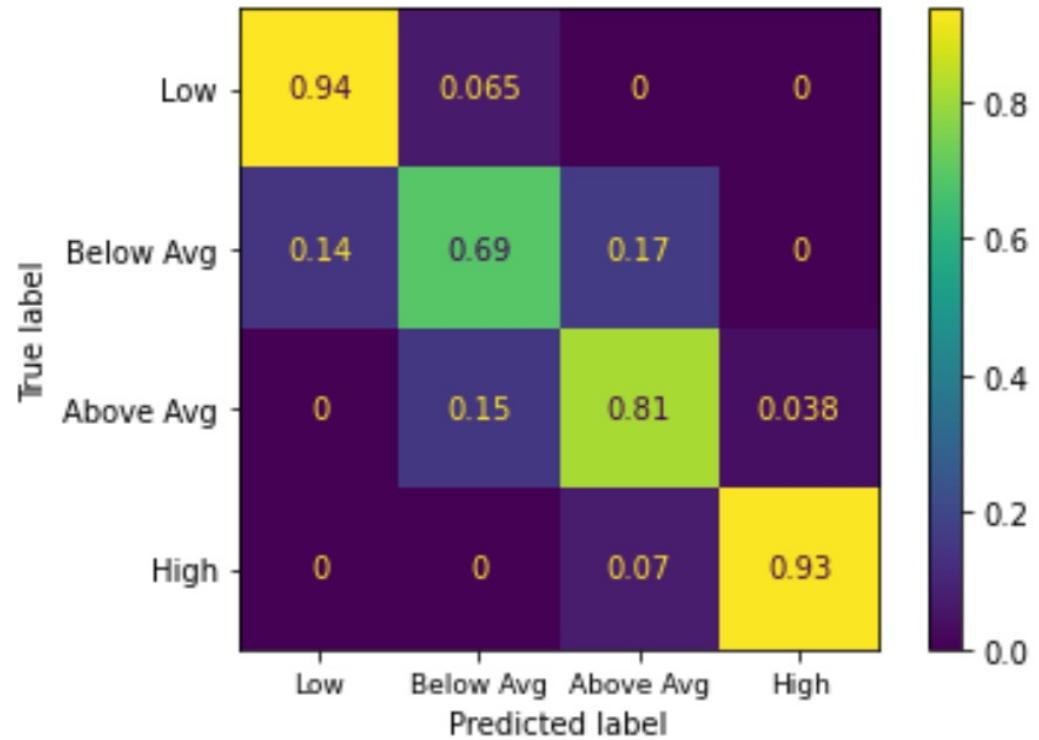
Final Model

- Accuracy Decreased a small amount
 - Minimal Overfitting
- Low Precision/Recall: Below-Avg
 - F1 score
 - Class imbalance issue?
- Indistinguishable below-avg and above avg?

	precision	recall	f1-score	support
Low	0.91	0.94	0.92	62
Below Avg	0.71	0.69	0.70	42
Above Avg	0.81	0.81	0.81	53
High	0.95	0.93	0.94	43
accuracy			0.85	200
macro avg	0.84	0.84	0.84	200
weighted avg	0.85	0.85	0.85	200

Evaluation

- Below average not as accurate
- Below Avg and Above Avg mistaken for each other
- Too Many Similarities?



Discussion

- Timeline Completed
 - January 17: Have Proposal Completed
 - January 24: Have all data collected
 - February 2: Finish Cleaning and Combining Datasets
 - February 15: Finish all Preprocessing and Outstanding Visualizations
 - February 19: Finish Comparing Potential Models
 - February 22: Tune Final Model and Test
 - February 27: Submit project with presentation
- Challenge: Time
 - Completed within 8 week
 - Would like more features
- Future work
 - Brand
 - Temporal Changes
 - Software

CALENDAR

					1	2	3
4	5	6	7	8	9	10	
11	12	13	14	15	16	17	
18	19	20	21	22	23	24	
25	26	27	28	29	30	31	

Conclusion

Cell Phone Evolution

Customers and Manufacturers
Need Smart Decisions

Best Value

References

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