Product Search Relevance Prediction

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Problem Statement

01

Business use search relevance to know about user sentiments and their preferences

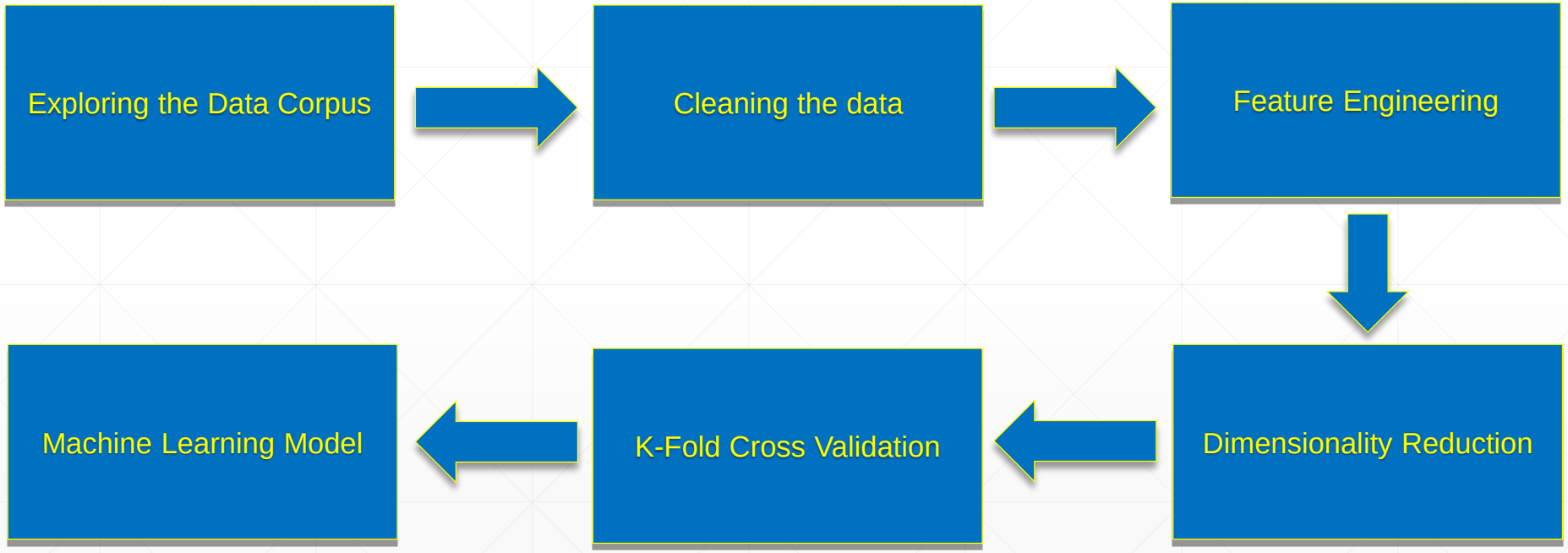
02

Front end: User reaches product in minimum texts
Back end: Use of Natural Language Processing

03

Home Depot : Use of machine learning algorithm to predict user intent and recommend potential product

Approach

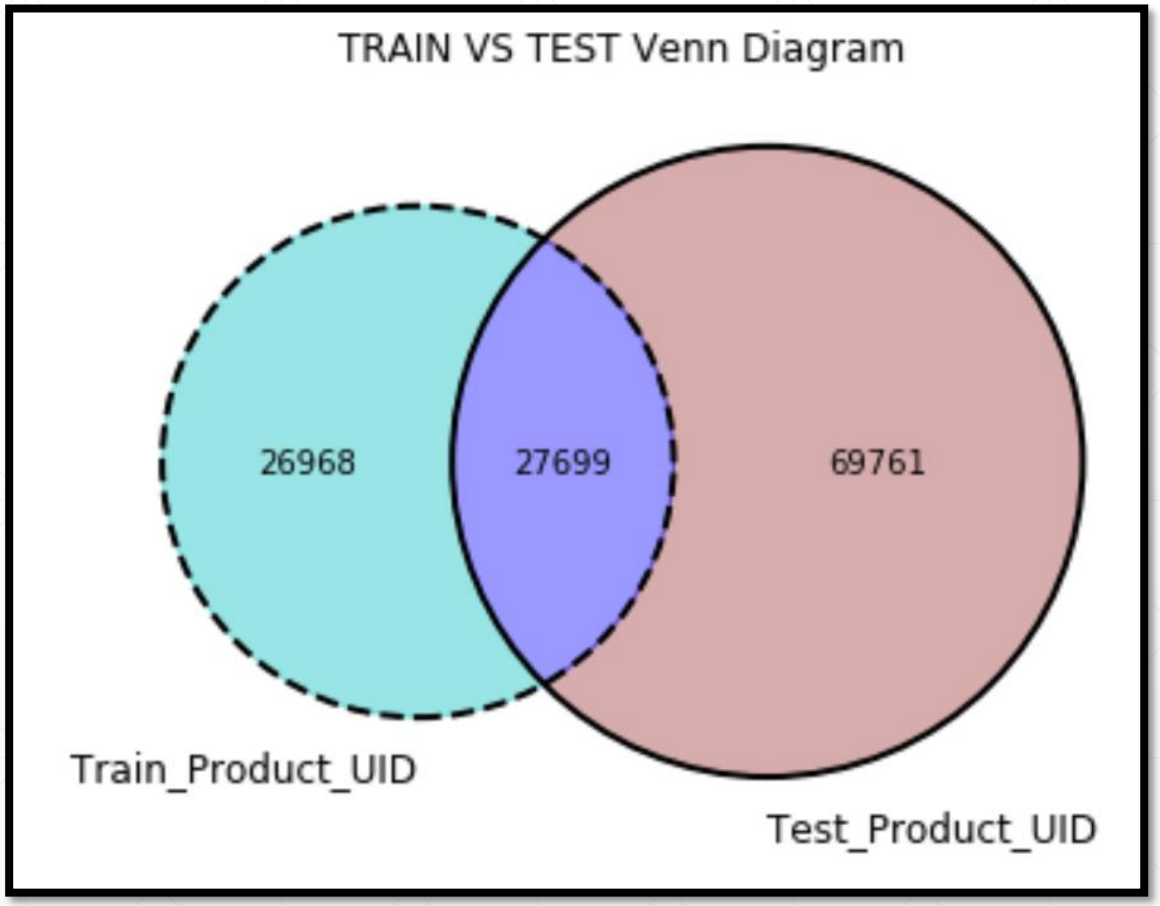

Exploring the Data Corpus
Cleaning the data
Feature Engineering
Dimensionality Reduction
K-Fold Cross Validation
Machine Learning Model

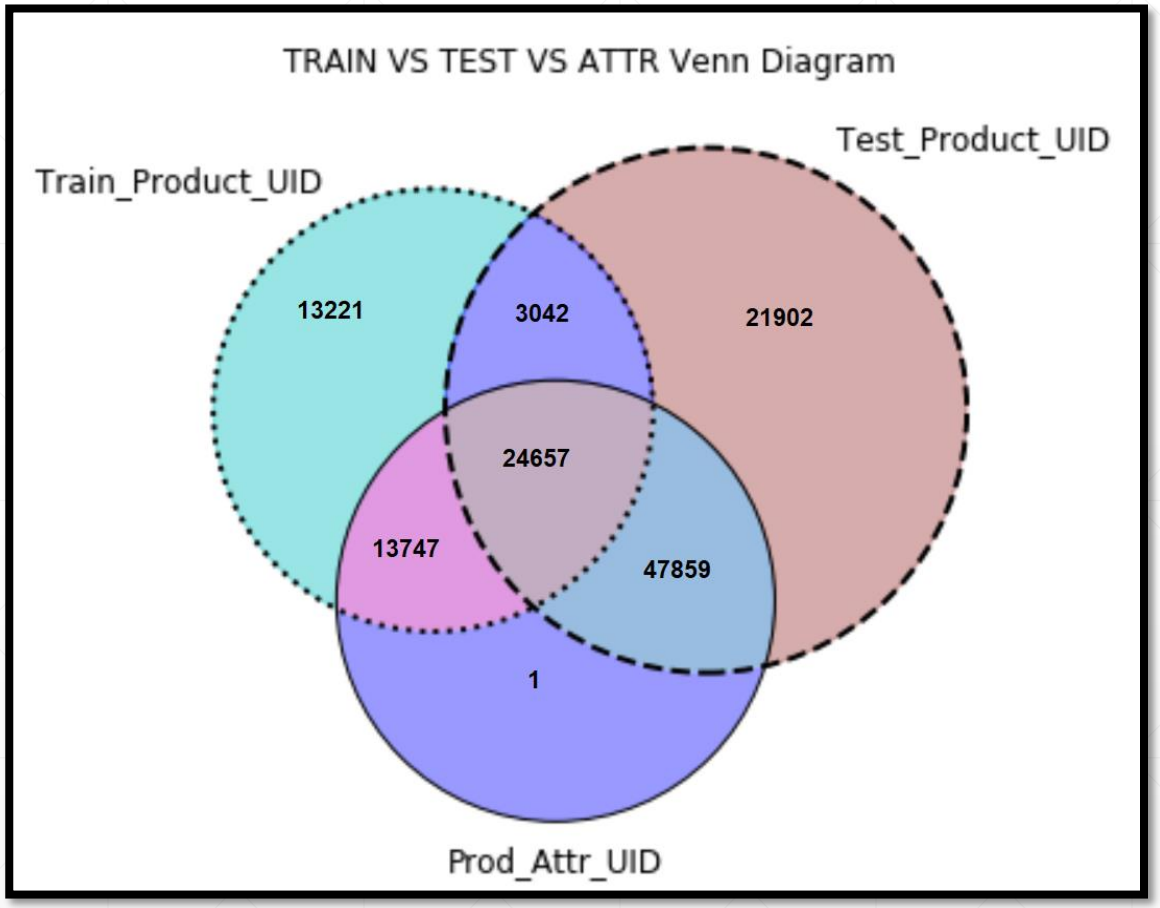
Exploring the Data Corpus

- **Datasets (Format *.csv)**
  - **Product** - There are 124428 products. Each product has a unique ID and a text description
  - **Attributes** - Most products are given extended information like bullet points of product functionality descriptions, size, color, brand, material, etc.
  - **Train Dataset** - Contains 74067 search/product pairs and their corresponding relevance scores
  - **Test Dataset** - Contains 166694 search/product pairs
  - **Relevance Scores -** Score 3 (perfect match), Score 2 (partially or somewhat relevant) and Score 1 (not relevant).
- **Evaluation -** The metric to evaluate the prediction errors is Root Mean Square Prediction Error (RMSPE)

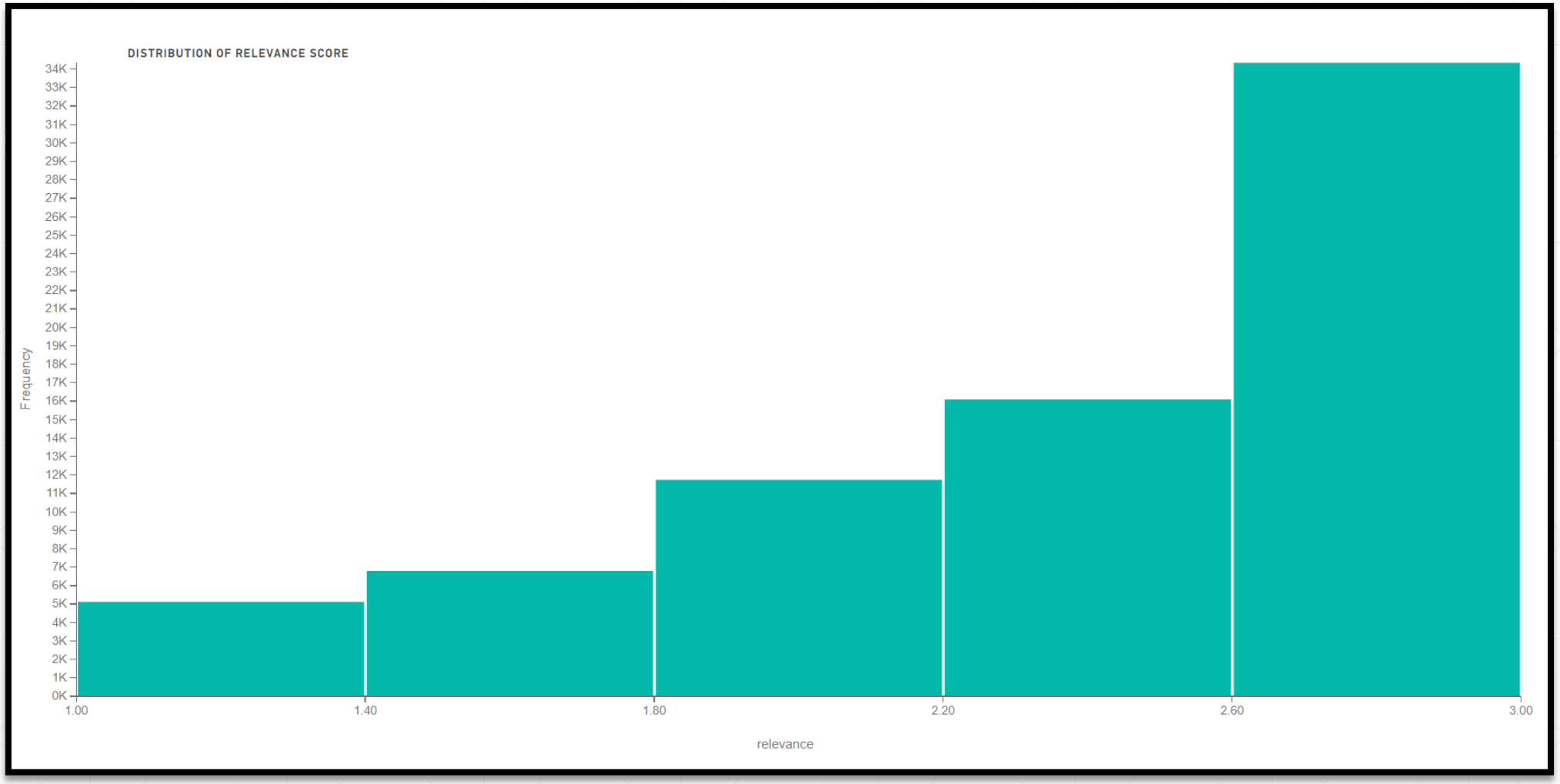
$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{actual} - \hat{y}_{predicted}\right)^2}$$

Product Intersection between Datasets

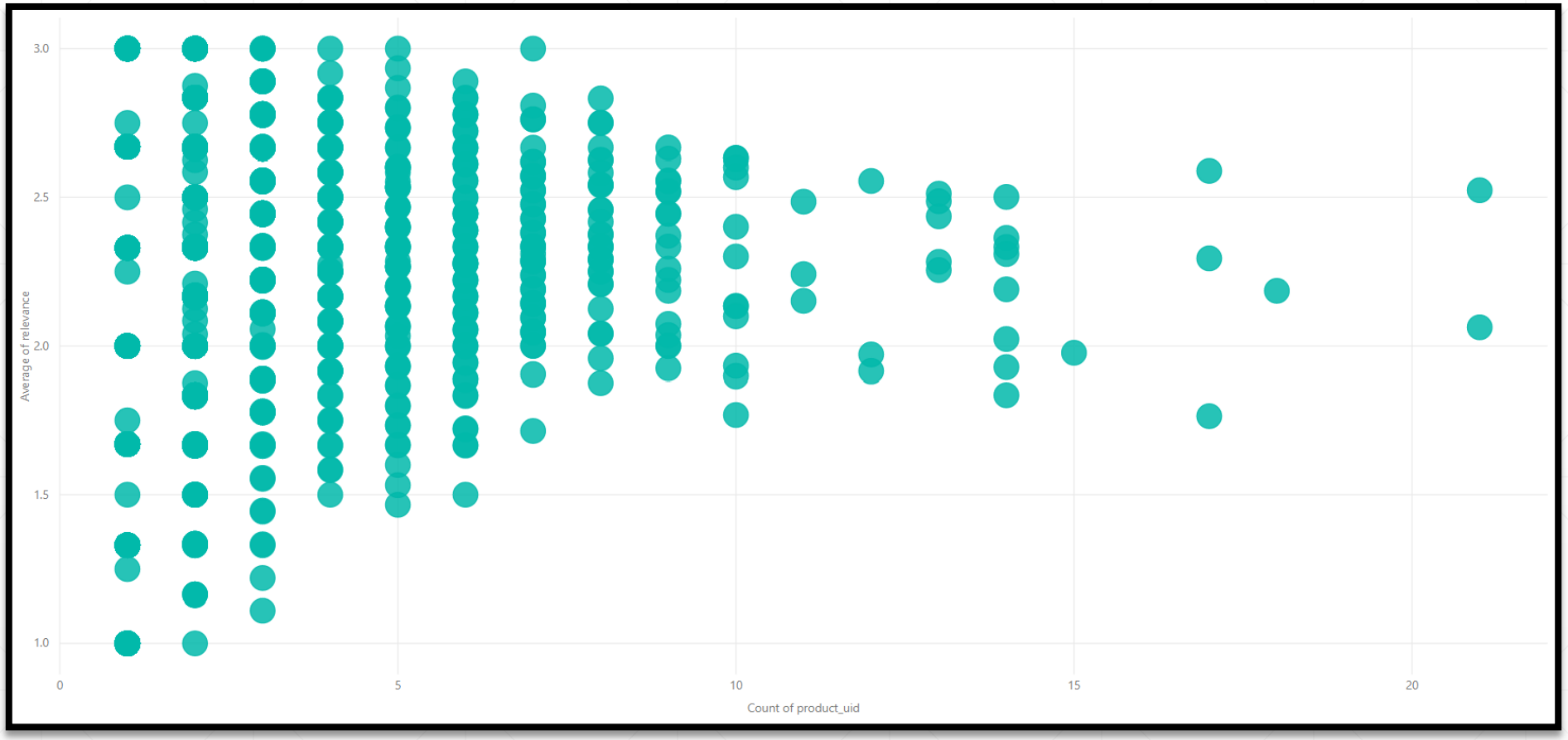




Distribution of Relevance Scores - Skewed

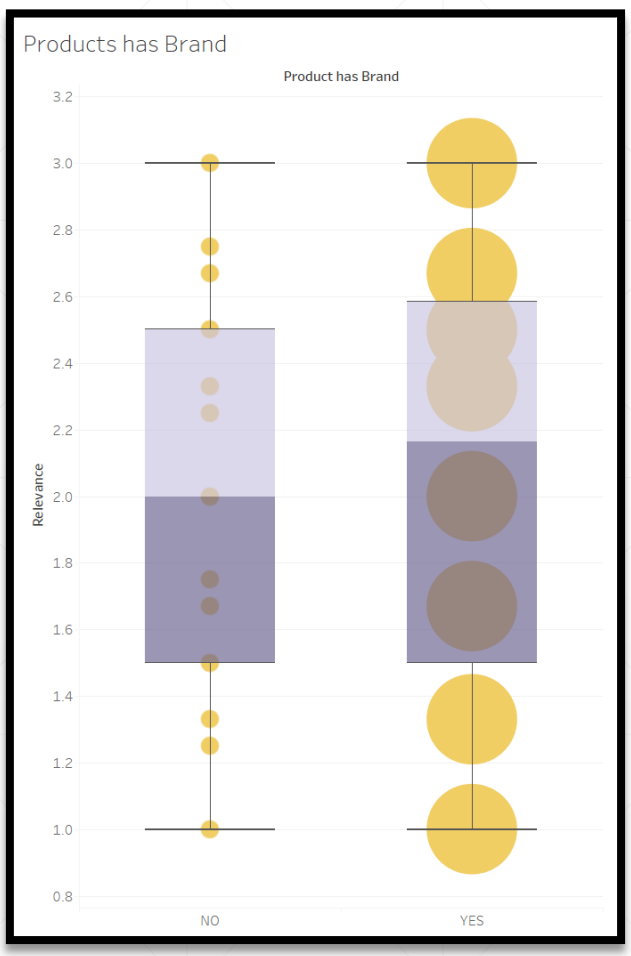


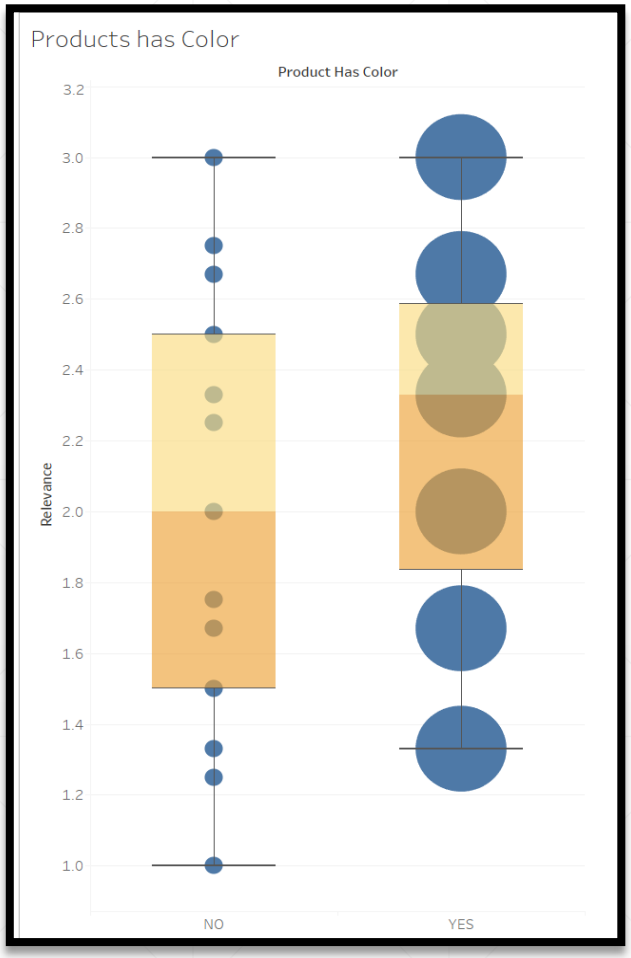
Distribution of Relevance Scores – Normalized

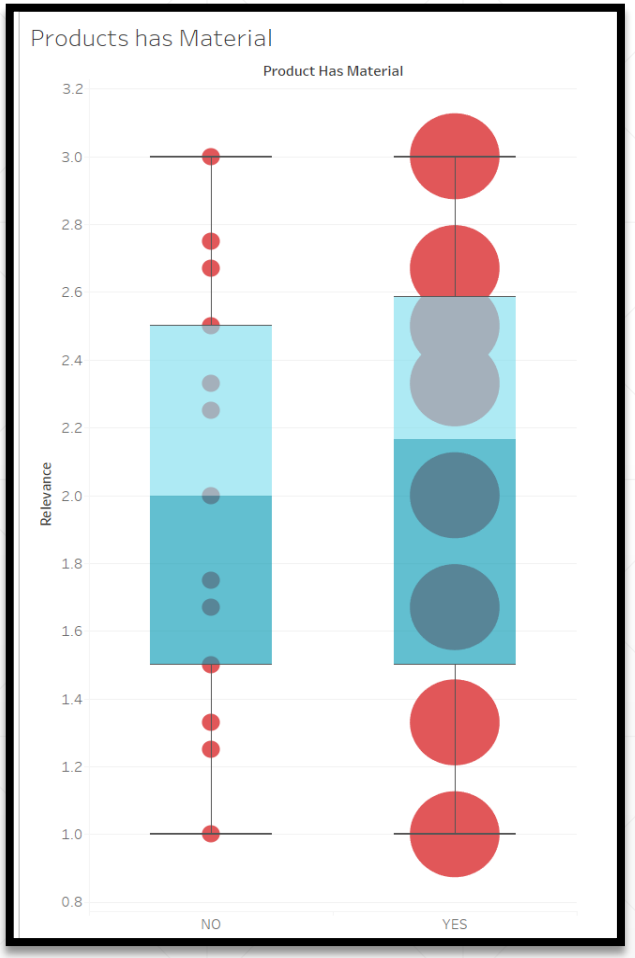


- As expected the variation of the **relevance** decreases as the number of times a *product_uid* occurs in the dataset. The **relevance** score is examined in the context of the number of parameters (words) in a **search_term**.

Include Product Attributes – Brand, Color, Material







Relevant Features

- Combine Train and Test dataset
- Add product description
- Append the product attributes of brand, color and material.

	C	D	E	F	G	H	I	J
1	relevance	product_title	product_uid	search_term	product_description	brand	color	material
2	3	simpson strong tie 12 gaug angl	100001	angl bracket	not onli do angl make joint stronger they also provid more consist straight corner sin	simpson strong tie	nan	galvan steel
3	2.5	simpson strong tie 12 gaug angl	100001	l bracket	not onli do angl make joint stronger they also provid more consist straight corner sin	simpson strong tie	nan	galvan steel
4	3	behr premium textur deckov 1gal	100002	deckover	behr premium textur deckov is an innov solid color coat it will bring your old weathe	behr premium textur deckov	brown tan tugboat	nan
5	2.33	delta vero 1 handl shower onli fa	100005	rain shower head	updat your bathroom with the delta vero singl handl shower faucet trim kit in chrom	delta	chrome chrome	nan
6	2.67	delta vero 1 handl shower onli fa	100005	shower onli faucet	updat your bathroom with the delta vero singl handl shower faucet trim kit in chrom	delta	chrome chrome	nan
7	3	whirlpool 1.9cu.ft. over the rang	100006	convect otr	achiev delici result is almost effortless with thi whirlpool over the rang microwav ho	whirlpool	stainless steel stainless	nan

- Character Case Conversion
- Tokenization
- Remove stop words
- Exclude Punctuation
- Deduct Special Characters
- Stemming
- Lemmatization
- Spell Check Dictionary

Cleaning the Data

- Length
  - Likelihood of two document* like search term and product title with disparate length being similar is low compared to document with similar length.
- Common words
  - Likelihood of a better relevance score for more common words between documents like search term and product attributes/title/description is higher than with less common terms.
- Cosine Similarity
  - Tokenizes → Computes the semantic importance of the tokenized word in the document (TF-IDF) → Vectorizes the TF-IDF weights → computes a cosine similarity vector product.
- Mean Similarity
- Fuzzy Wuzzy Ratios
  - Includes spelling mistakes, to understand customers intent.

Feature Engineering

Using Natural Language Processing, to transform text corpus into computational format.

* Document – set of words like in a search term.

- Total extracted explanatory features are 38.
- Response feature is relevance score
- Objective is to penalize those explanatory features that add noise to the variance of relevance score
- Use LASSO,
  - **L**asso **A**bsolute **S**hrinkage & **S**election **O**perator
  - Regression Analysis method
  - Performs variable selection
  - Enhances prediction accuracy
  - Improves Interpretability of the statistical model.
- Post LASSO, the improved model contains 27 explanatory features.

Dimensionality Reduction

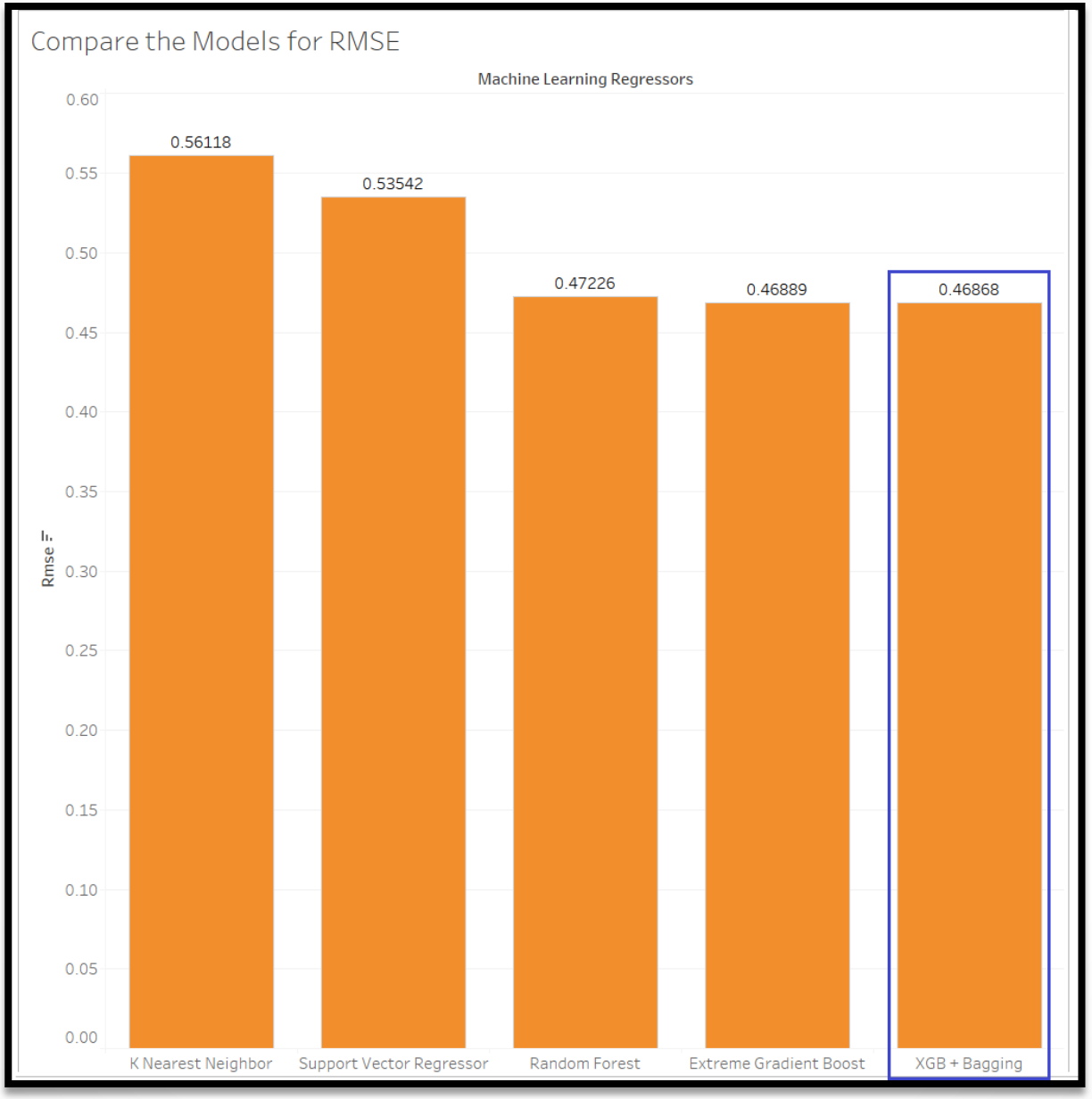
By using statistical representation that can describe most but not all of the variance within the data, thereby retaining the relevant information, while reducing the amount of information necessary to represent it.

- To avoid underfitting or overfitting of the prediction curve
- Approach is to fit the model for ‘K’ number of times*
  i. Randomly split the train dataset in 80% train and 20% test
  ii. Train the model with different regressor algorithms
  iii. Test the model
  iv. Validate the prediction by computing the RMSE, for i = 1
  v. Repeat steps i to iv, for i = K times
  vi. Compute the Mean of RMSEs to find the optimal model
  vii. Compare the mean RMSEs of regressors (next slide)
  viii. Select the algorithm producing the minimum root mean square error.
- The best regressor predicts the relevance score for the Kaggle’s test data with minimum prediction error.

K-Fold Cross Validation

Achieve generalized predictive model

* Optimal K = N/(0.20*N), N is size of Train Dataset



Results

eXtreme Gradient Boosting + Bagging Regressor

Key Takeaways

- The prediction error is high, making the model impractical in business use
- The high error also means that there are other explanatory features that influence the product search relevance scores derived by the customer

Future Implications:

- More advanced features making the search experience for users more convenient.
- Can also take polarity of words into consideration.
- NLP can be used beyond the search optimization in detecting the sentiment and emotion of the user towards the product and based on this predict the market share of the brand.
- Can be used in conversational speech where we machine listens to our conversation and answers to the questions asked. Wolfarm and Microsoft are working on this technology.

Appendix

- Scripting Language – Python and R
- Visualizations – Tableau, Power BI, matplotlib and ggplot2 packages
- Packages – numpy, pandas, nltk, sklearn, fuzzywuzzy, genism, spaCy, fastText
- Competition - https://www.kaggle.com/c/home-depot-product-search-relevance
- GitHub – https://github.com/kedarwagh
- LinkedIn – https://www.linkedin.com/in/kedarwagholikar
- Kaggle - https://www.kaggle.com/kdanalytics/kernels