Sales Forecast: Sporting Goods

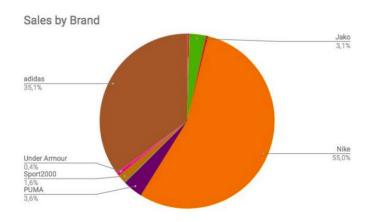


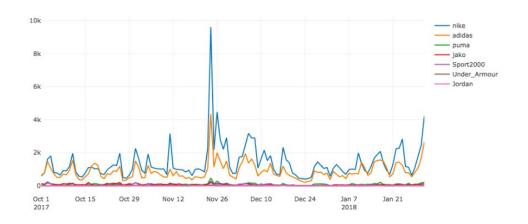
- Adila Aghazada
- Bengi Koseoglu
- Chowdhury, Abdullah Al Murad
- Khizer Naushad
- Na Gong
- Qian Xia
- Sanjita Suresh

- 1. Data Exploring
- 2. Feature Engineering
- 3. Clustering
- 4. Modeling

- 1. Data Exploring
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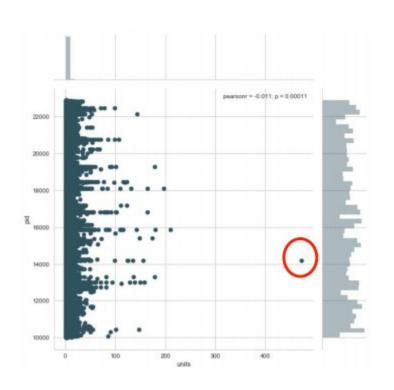
Data Exploration







Outlier Detection





- 1. Data Exploring
- 2. Feature Engineering
- 3. Clustering
- 4. Modeling

Feature Engineering

- Weather Data (from team 6)
- AccuWeather
- 11 Team Sports (from team 5)
- 11TEAMSP TRTS

- Holidays
- Weekends
- Size: new_size, size_classification
- New_product
- Price_daily_change
- Sum_unit_previous_month

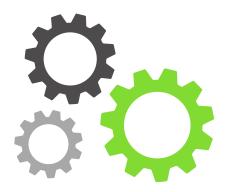
Dummy Features

Categorical At 🕶	Dummy Attribute	~
color	schwarz, blau, gruen, weis, braun, lila, grau,	
brand	Nike, PUMA, adidas, Jako,	
mainCategory	maincat_1, maincat_9, maincat_15	
category	cat_2, cat_7, cat_16, cat_33,	
subCategory	subcat_0, subcat_3, subcat_5, subcat_6,	
size	size_S, size_M, size_L, size_XL,	
	•••	

(>300 features)

Long Format

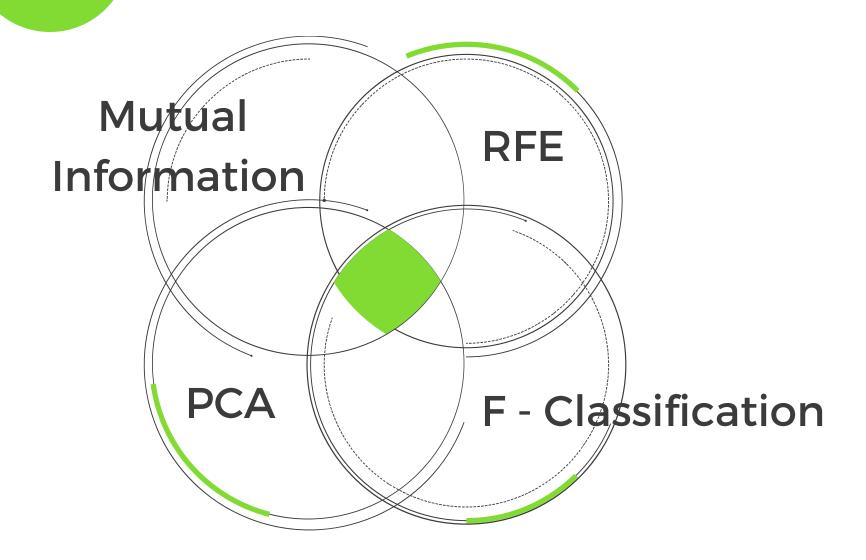
Product	Sales Date	Units
10063 L	2017-10-04	12
10063 L	2017-10-11	1
10063 L	2017-11-20	3
10063 L	2017-11-30	4



Product	Sales Date	Units
10063 L	2017-10-01	0
10063 L	2017-10-02	0
10063 L	2017-10-03	0
10063 L	2017-10-04	12
10063 L	2017-10-05	0
10063 L	2017-10-06	0
10063 L	2017-10-07	0
10063 L	2017-10-08	0
10063 L	2017-10-09	0
10063 L	2017-10-10	0
10063 L	2017-10-11	1
10063 L	2017-10-12	0
10063 L	2017-10-13	0
10063 L	2017-10-14	0

Xia; Bengi; Gong

Features Selection



Bengi; Gong

Features Selection

3

- mainCategory 15
- mainCategory_9
- Category_16
- Category_18
- Category_7
- subCategory_0
- subCategory_32



- mainCategory_1
- Category_10
- Category_2
- Category_33
- Category_37
- subCategory_16
- subCategory_3
- new_product

Correlation Matrix



- 1. Data Exploring
- 2. Feature Engineering
- 3. Clustering
- 4. Modeling

Clustering Approaches

- **BRAND**
 - Nike
 - Adidas
 - PUMA
 - Jako
 - Others brands

- **CATEGORY**
 - mainCategory_1
 - mainCategory_9
 - mainCategory_15

- **3** SALES
 - low sales
 - average sales
 - good sales
 - top sales
 - new in Jan



K-Means Clustering

Use the selected features with Oct-Dec data:

- Decide the optimal cluster number:
 - calinski_harabaz_score = 7
 - elbow analysis = 12
- K-means clustering: k = 7



Time Series Clustering

Dynamic Time Warping

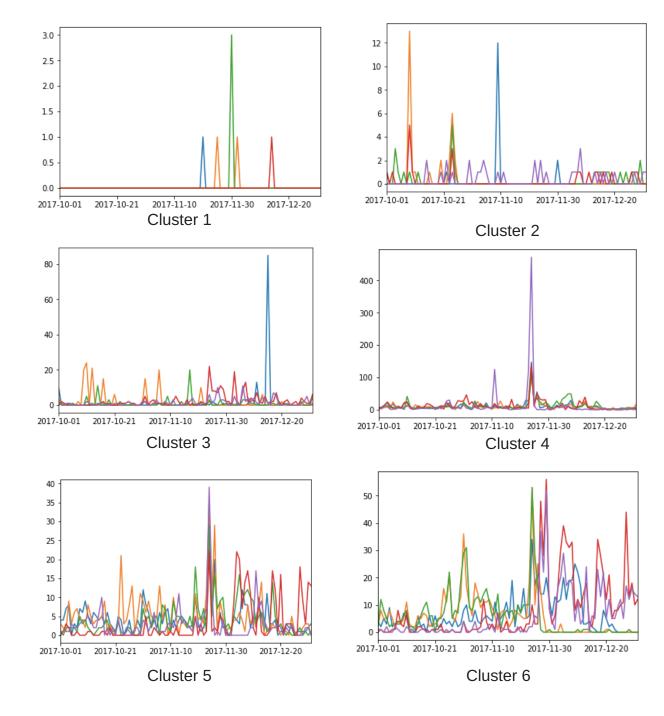


Hierarchical Clustering



7 Clusters





200 -150 -100 -50 -2017-10-01 2017-10-21 2017-11-10 2017-11-30 2017-12-20 Cluster 7

Clustering Comparison

Clustering	Performance
K-Means	280
Category	276.7
Brand	276.1
Time Series	261



- 1. Data Exploring
- 2. Feature Engineering
- 3. Clustering
- 4. Modeling



- January 15th
- Error function:
- Baseline = 261.02

$$E = \sqrt{\sum_{i} |d_{i} - \hat{d}_{i}|}$$

Test 0	260,77
Test 1	260,88
Test 2	261,50
Test 3	260,99
Test 4	260,92
Average	261,02
Standard Dev.	0,26



pid =	size =	oct_opening =	sales_oct =	nov_oepning =	sales_nov =	dec_opening =	sales_dec =	jan_openinį =	sales_ja =	feb_openi =
10000	XL (158-170)	2	0	2	1	1	0	1	0	
10001	L	5	0	5	1	4	1	3	2	
10003	3 (35-38)	16	1	15	14	1	0	1	0	
10003	4 (39-42)	4	0	4	3	1	0	1	0	
10003	5 (43-46)	12	7	5	0	5	3	2	1	
10006	XL	2	0	2	0	2	1	1	0	
10008	XL	18	0	18	2	16	0	16	4	1
10013	L	2	0	2	0	2	0	2	1	
10013	M	5	0	5	0	5	1	4	3	
10013	S	2	0	2	1	1	0	1	0	
10015	L	7	1	6	1	5	0	5	0	
10015	S	2	0	2	0	2	1	1	0	
10017	L	5	1	4	3	1	0	1	0	
10020	XL	5	0	5	3	2	0	2	1	

Stock Calculation



Xia; Bengi; Gong: Murad



- Feature: total_sales_current_month
- Cluster: sales binning
- Model: GBoost Regression
- Error = 203.6





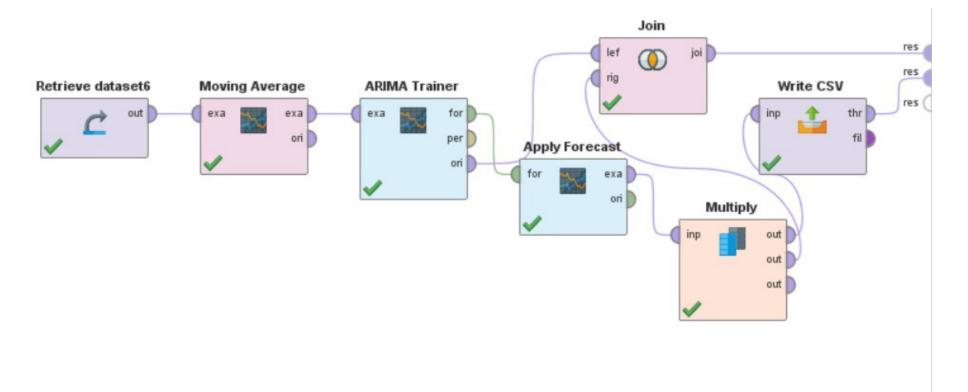
- 1. Handle Missing Values
- 2. Predicting decimals
- 3. January 31st -> January 22nd
- 4. Remove Black Friday
- 5. Based on Time Series Clustering
- 6. Regression Parameter Tuning
- 7. Cluster-based Model Combination
- 8. Ensemble stacking

Model Approaches

- 1. ARIMA
- 2. Windowing
- 3. Regression
- 4. Combine Model
- 5. Ensemble



ARIMA Model



Model	Average Performance	Standard Dev.
Arima all	262,034	0,50
Arima Time Clustering	248,928	0,34

Windowing Model

Model	Average Performance	Standard Dev.
Windowing Individually Lag(1)- Linear Reg	256,621	0,65
Windowing Individually Lag(30)- Linear Reg	264,042	4,16
Windowing Individually Lag(30)- ANN	259,428	0,22
Windowing Individually & Weather Data (Lag=1)- Regr	253,125	0,33
Windowing Individually & Weather Data (Lag=1)- ANN	268,706	0,31
Windowing Time Series Clustering (Lag=1)- Regr	254,947	0,35
Windowing Time Series Clustering (Lag=5)- Regr	256,922	0,36
Windowing Time Series Clustering (Lag=10)- Regr	254,988	0,34
Windowing Time Series Clustering (Lag=15)- Regr	254,822	0,30
Windowing Time Series Clustering (Lag=20)- Regr	252,602	0,30
Windowing Time Series Clustering (Lag=20)- ANN	250,848	0,37
Windowing Time Series Clustering (Lag=30)- Regr	266,374	0,38
Windowing Time Series Clustering (Lag=30)- Gradiant Boost	259,160	0,31
Windowing Time Series Clustering (Lag=30)- Random Forest	257,716	0,32

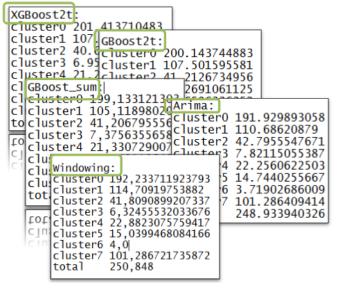


LRegression	308.6		
GBRegression	285.7		
DTRegression	293.5		
RFRegression	293.9		
WeekdayRegression	276		
-			
K-Means	280		
Category	276.7		
Brand	276.1		
TimeSeries	261		
+			
GBoost & XGBoost +	TS Cluster		
Parameter Tu	ning		

Cluster	Parameter - Gboost					
2	'learning_rate': 0.05, 'max_depth': 3, 'min_samples_split': 2, 'n_estimators': 500}					
3	{'learning_rate': 0.05, 'max_depth': 3, 'min_samples_split': 10, 'n_estimators': 1000}					
4	{'learning_rate': 0.01, 'max_depth': 10, 'min_samples_split': 5, 'n_estimators': 100}					
5	{'learning_rate': 0.05, 'max_depth': 3, 'min_samples_split': 2, 'n_estimators': 100}					
6	{'learning_rate': 0.01, 'max_depth': 15, 'min_samples_split': 10, 'n_estimators': 100}					
- 1	T consumpte uptice a violy reunting rate a violy max upper any minimum reigns aby in exemplators about superior and response and a superior a					
	5 ('colsample_bytree': 0.7, 'learning_rate': 0.03, 'max_depth': 6, 'min_child_weight': 7, 'n_estimators': 500, 'objective': 'reglinear', 'silent': 1, 'subsample': 0.8					
	6 ('colsample_bytree': 0.8, 'learning_rate': 0.03, 'max_depth': 6, 'min_child_weight': 7, 'n_estimators': 500, 'objective': 'reg/linear', 'silent': 1, 'subsample': 0.7					
	7 ['colsample_bytree': 0.8, 'learning_rate': 0.03, 'max_depth': 9, 'min_child_weight': 6, 'n_estimators': 500, 'objective': 'reg:linear', 'silent': 1, 'subsample': 0.7					
- 17	7 ['colsample_bytree': 0.8, 'learning_rate': 0.03, 'max_depth': 9, 'min_child_weight': 6, 'n_estimators': 500, 'objective': 'regilnear', 'silent': 1, 'subsample': 0.7					
	6 (coisample_bytree: 0.8, learning_rate: 0.03, max_depth: 0, min_chiid_weight: 7, in_estimators: 500, objective: regimear, silent: 1, subsample: 0.7					

Model	Average Performance	Standard Dev.
GBoost Regression	253.6	0,59
GBoost Regression_sumunit	251.7	0,45
XGBoost Regression	254.4	0,66







Model	Average Performance	Standard Dev.	
Ensembling Stacking-1	250.9	0,61	
Ensembling Stacking-2	253.8	0,59	

Bengi; Gong: Xia

Model	Average Performance	Standard Dev.
Combine Model-1	248.7	0,33
Combine Model-2	247.0	0,37
Combine Model-3	246.8	0,34
Combine Model-4	245.8	0,37



cluster 1	ARIMA
cluster 2	GBoostRegression_sumUnits
cluster 3	XGBoost Regression
cluster 4	Windowing Time Series Clustering (Lag=20)- ANN
cluster 5	XGBoost Regression
cluster 6	GBoostRegression_sumUnits
cluster 7	Windowing Individually Lag(30)- Linear Reg
cluster 8	GBoost Regression

February Prediction



pid|size|soldOutDate 15835|39 1/3|2018-02-22 15835|40|2018-02-03 15835|41 1/3|2018-02-10

Column name	Value range
pid	Natural number
size	String
soldOutDate	Format YYYY-MM-DD

pid|size|soldOutDate 10000|XL (158-170)|2018-02-18 10001|L|2018-02-18 10003|3 (35-38)|2018-02-11 10003|4 (39-42)|2018-02-18 10003|5 (43-46)|2018-02-18 10006|XL|2018-02-18 10008|XL|2018-02-22 10013|L|2018-02-22 10013|M|2018-02-18

12824 * 3

SoldOutDay_predict.dtypes

pid int64
size object
soldOutDate datetime64[ns]

Bengi; Gong; Sanjita

MANY THANKS