PIZZA RESTAURANT DATA ANALYSIS PROJECT

Ironhack week 7: Machine learning

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Project workflow

Data cleaning + preparation

Time series prediction

Categorical

Insight generation + plotting

Conclusions

Business case

- Predict peak times to optimise staffing
  - Track seasonality in different time periods: daily, weekly, monthly and yearly
  - Adjust staffing levels to maximise output at peak times and utilisation during troughs
  - Use seasonal insights to generate ideas for promotional activity
- Predict customer choices to gain insights for ingredient purchasing
  - Predict purchasing patterns in type, name, size and price to enable smart ordering practices for ingredients.
  - Give insights about the accuracy of the model for the different variables

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SECTION

Optimising staffing

Using Meta’s Prophet model to forecast time series data

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Models Used

- Prophet (Meta)

Meta

Functions

- Sklearn style .fit/.predict
- Seasonality forecasts
- Cross validation for MAE values

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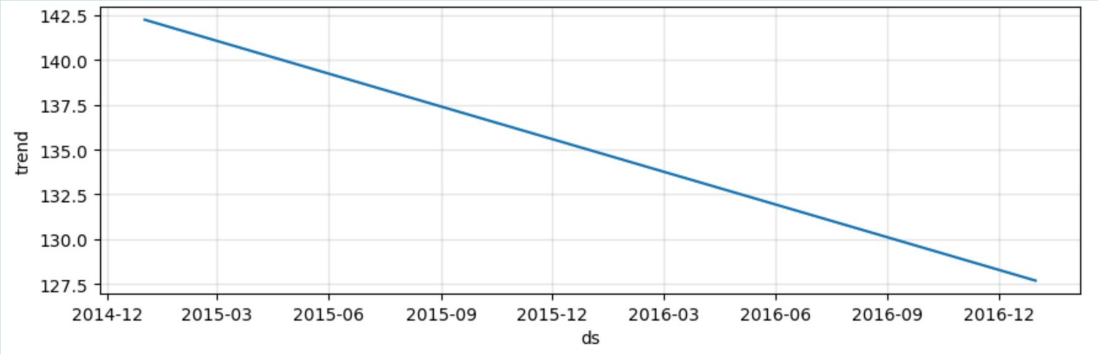
Forecasting daily orders

- Concerning downward trend in order volume across the year



- Able to forecast future order volumes with some accuracy:
  - 30 days: MAE 18.6 (13.4%)
  - 60 days: MAE 25.0 (18.1%)
  - 90 days: MAE 33.8 (24.4%)

Mean daily orders: 138

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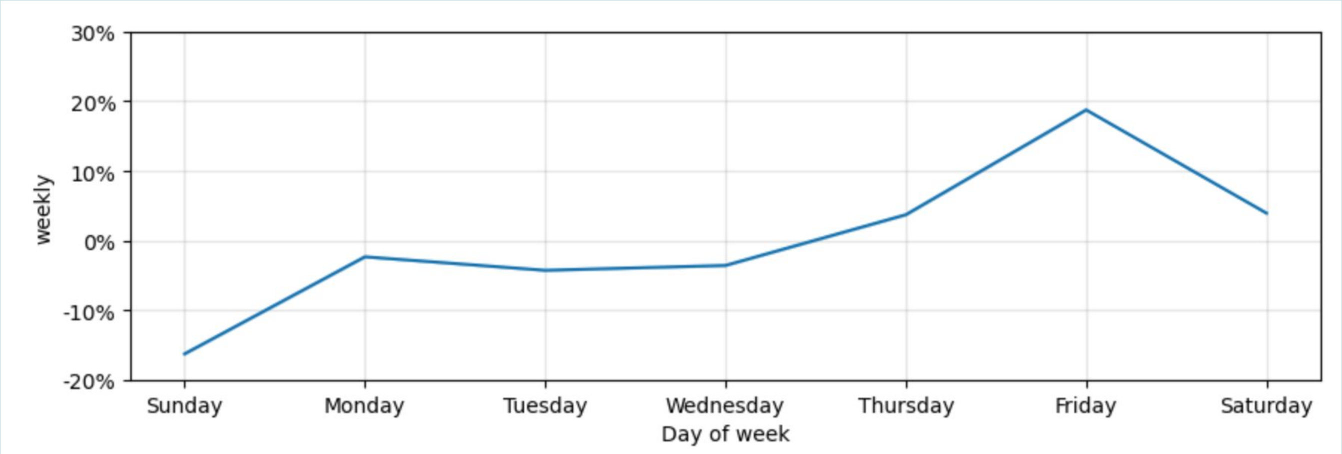
Tracking weekly patterns

- Natural increase of 15% in order volume for “pre-weekend” period (Thursday-Saturday)



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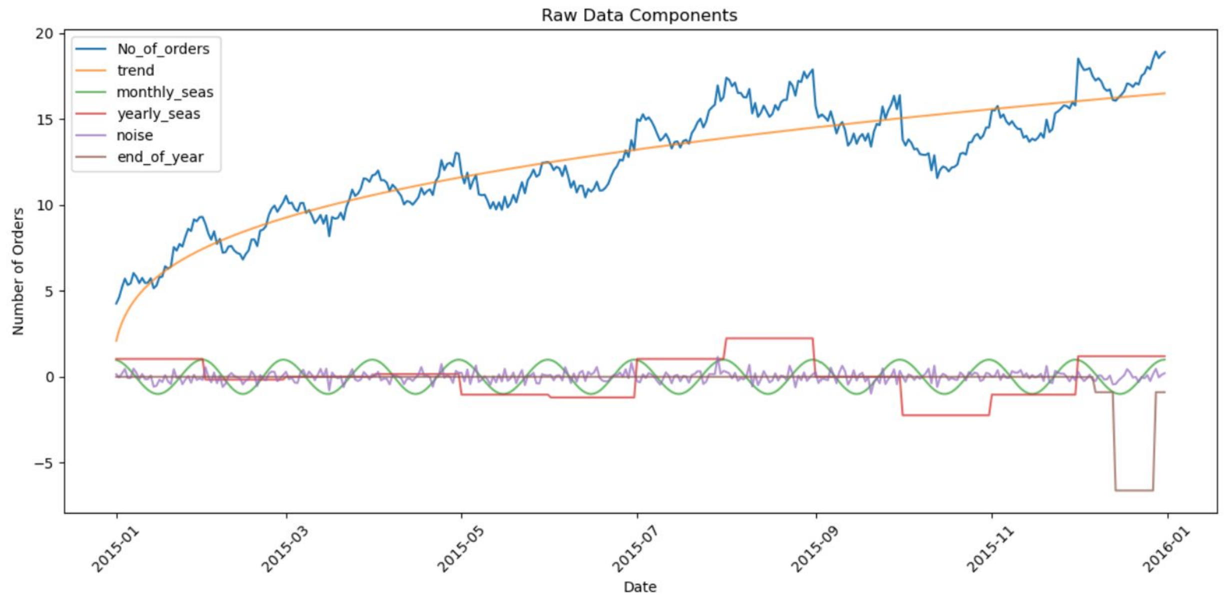
Monthly seasonality

- Distinct seasonal peaks in sales—particularly in August and towards the end of the year



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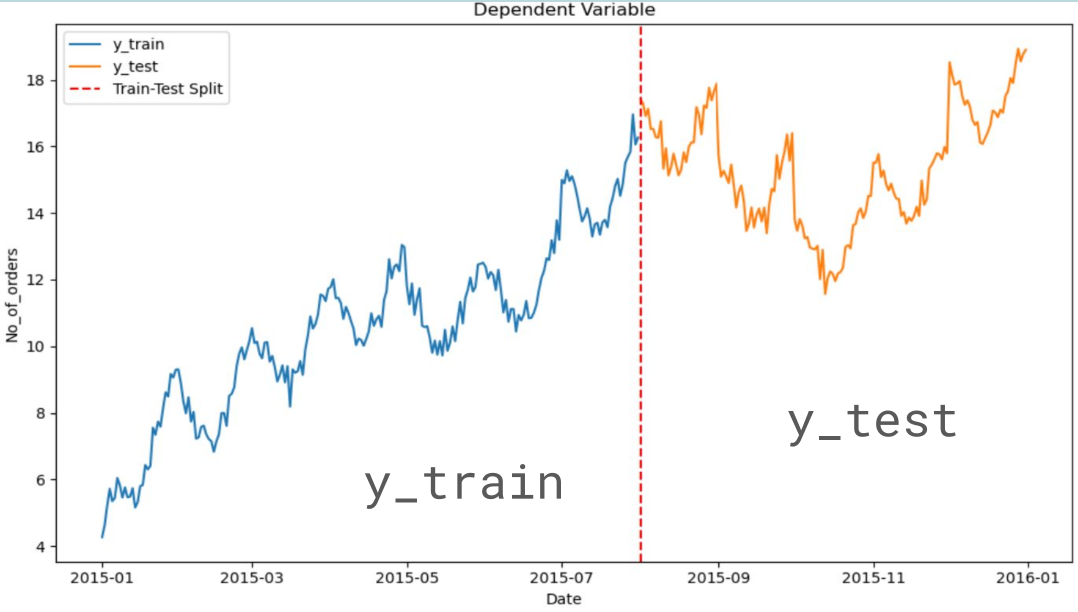
Monthly seasonality

- Evaluating our model : threshold “2015-08-01”



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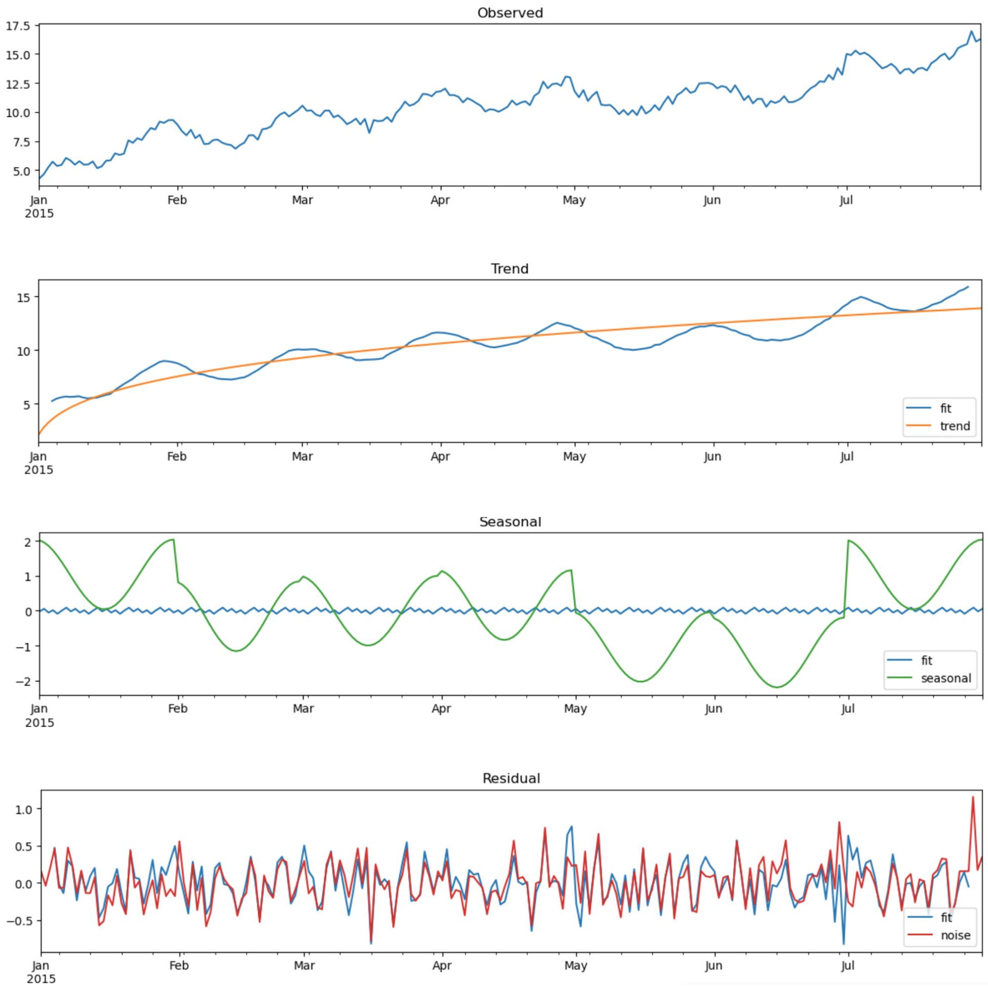
Time Series Decomposition

Because time series often exhibit different patterns, **decomposition** can be used which breaks the time series down into **four parts**: observed data, trend, seasonal and remainder/residual.



SECTION

Mapping customer choices

- Categorical data transformation
- **Comparing methods**: KNN, Bagging, RFM, AdaBoost, Gradient Boost
- **Goal**: get the most accurate method/model
- Most optimal **hyperparameter**

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Categorical Data Transformation

Methodologies used:

- One Hot Encoder to dummify categorical columns’ values 1 by 1
- Dictionaries and the use of map in pizza columns to values

[size]	[type]	[name]
S	Veggie	Margerita
M	Classic	Calabrese
L	Supreme	Pepperoni
XL	Chicken	[...]
XXL		

One Hot Encoding / Dictionary mapping

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Findings

Using OneHotEncoder and then applying the k-nearest neighbors (KNN) algorithm to predict **pizza sales patterns**.

- Column [name] had an R^2 score of **0.23**.
    - **Insight**: [name] of pizza had low predictive power.
- Column [size] had an R^2 score of 1.00.
    - **Insight:** The [size] variable has moderate predictive power in this dataset which is close to 1. When we calculated size without relation to **pizza price** R^2 was closer to **0.47** so its very dependent on this.
- Column [type] had a perfect score of **1.00**
    - **Insight:** This is unusual and could be a sign of overfitting.

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Models Used

- K-Nearest Neighbors
- Linear Regression
- Decision Trees

Ensemble Techniques

- Bagging and Pasting
- Random Forest Method
- Gradient Boosting
- Ada boost

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After comparing we found...

- **Random forest** was the best **ensemble method** according to the R2 score but it was still near to 0.36 for column **name** but near to 1.00 for [size] and [type].

- After several tries with the **Grid Search model** we have estimated that the optimal “**depth**" is 10 and "**max leaf nodes**" is 40.

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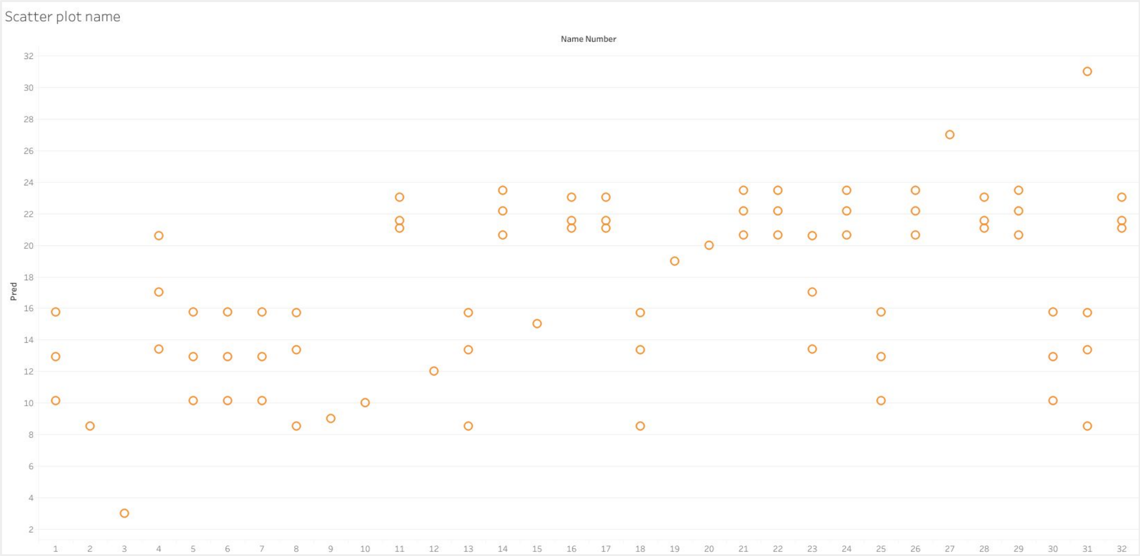
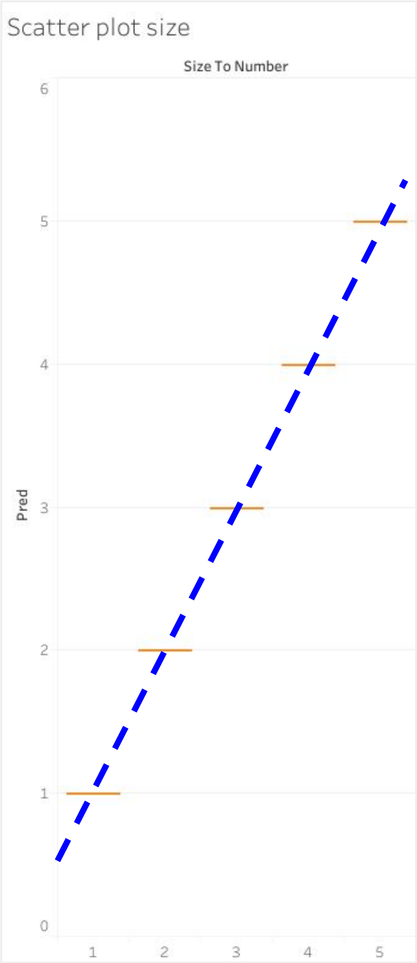
Plotting [size] and [name]





Correlation

Biggest correlation in price with [size] and [type]

Almost no relation between the variables so probably will have a low R^2 value

Heatmap Correlation

Variables	Name Number	Price	Size To Number	Type To Number	Weekday Nº
name_number	1,0000	0,0853	0,1074	0,1471	0,0002
price	0,0853	1,0000	0,8843	0,2906	[illegible]
size_to_number	0,1074	0,8843	1,0000	0,0758	0,0079
type_to_number	0,1471	0,2906	0,0758	1,0000	[illegible]
weekday nº	0,0002	0,0100	0,0079	0,0032	1,0000

SECTION

Conclusions

How can Perfectly Distributed Pizza use these insights to generate more profit in 2016?

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Optimise staffing

Time series predictions suggest that PDP's order volume will continue to decrease through 2016

Weekly seasonality makes a clear case for additional staffing on Thursday, Friday and Saturdays

Underperformance in June and October suggest indicative windows for promotional activity

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Smart inventory management

Pizza dough predictions would make PDP able to optimize its inventory

However, modelling demand by [name] showed unpredictable demand as demonstrated by the low R^2 value

Categorical columns also showed limited correlation suggesting each should be analysed individually by volume

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Thank you

Have a slice on us!

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