Choosing the Algorithm

FEATURE ENGINEERING WITH PYSPARK

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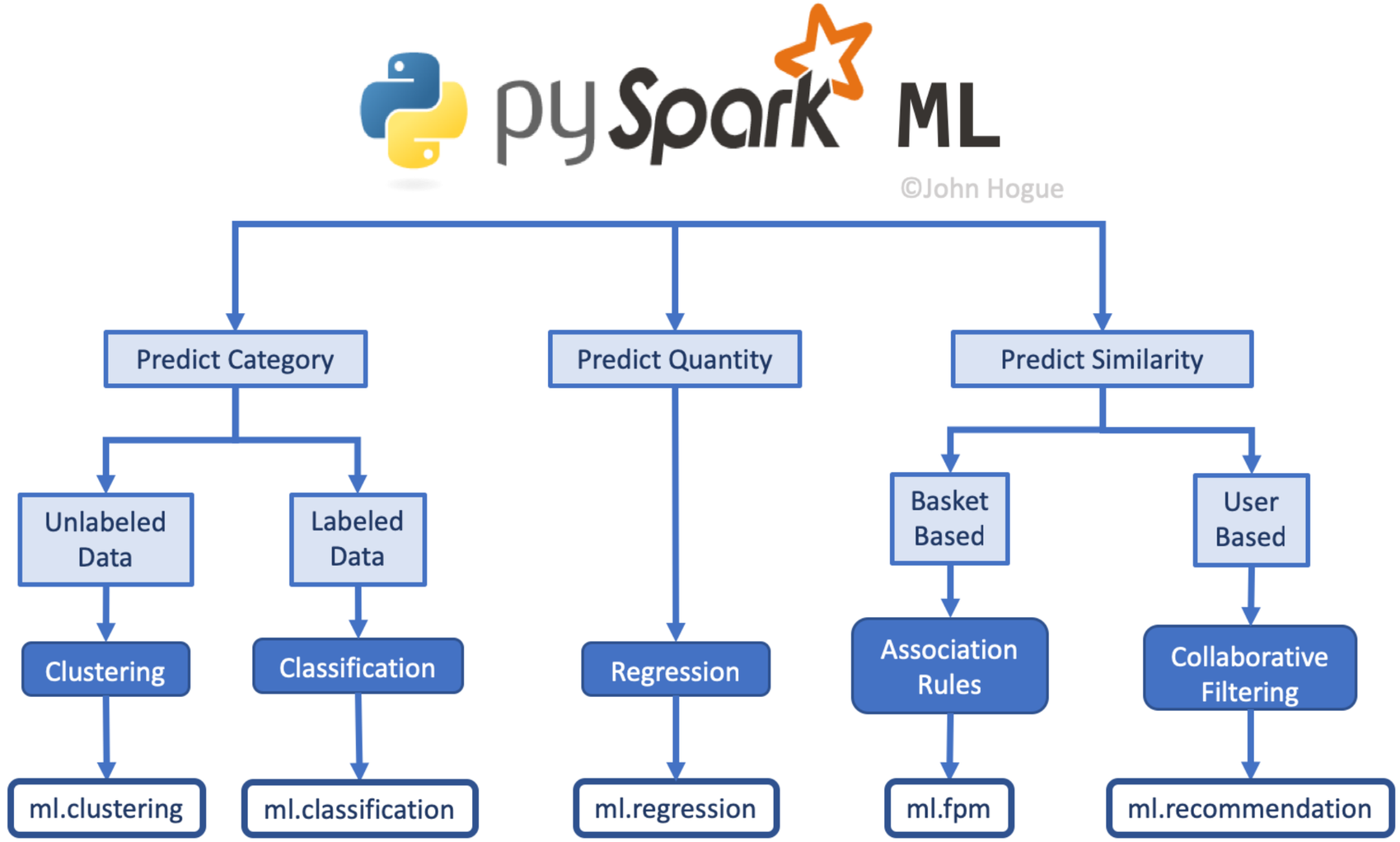
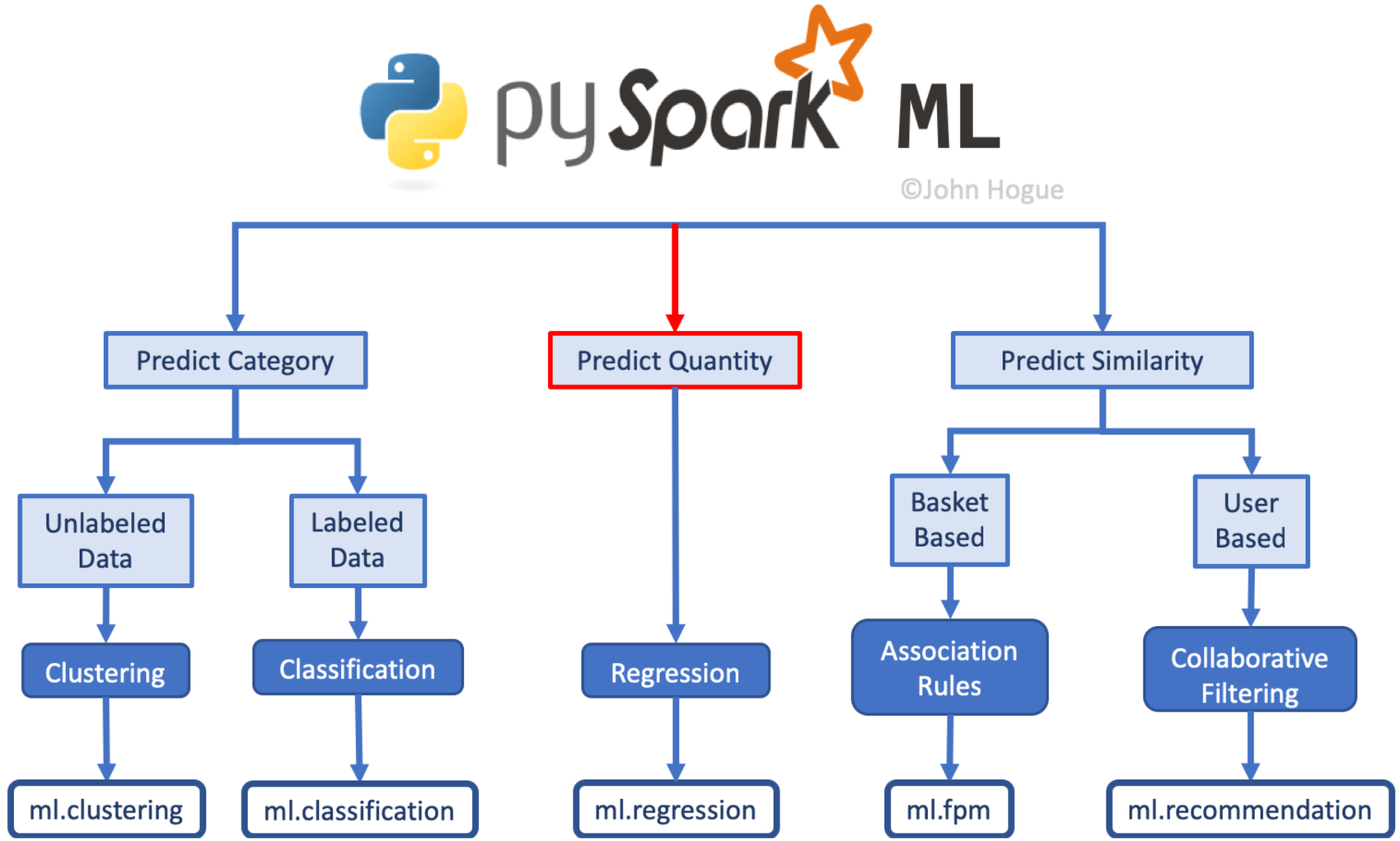
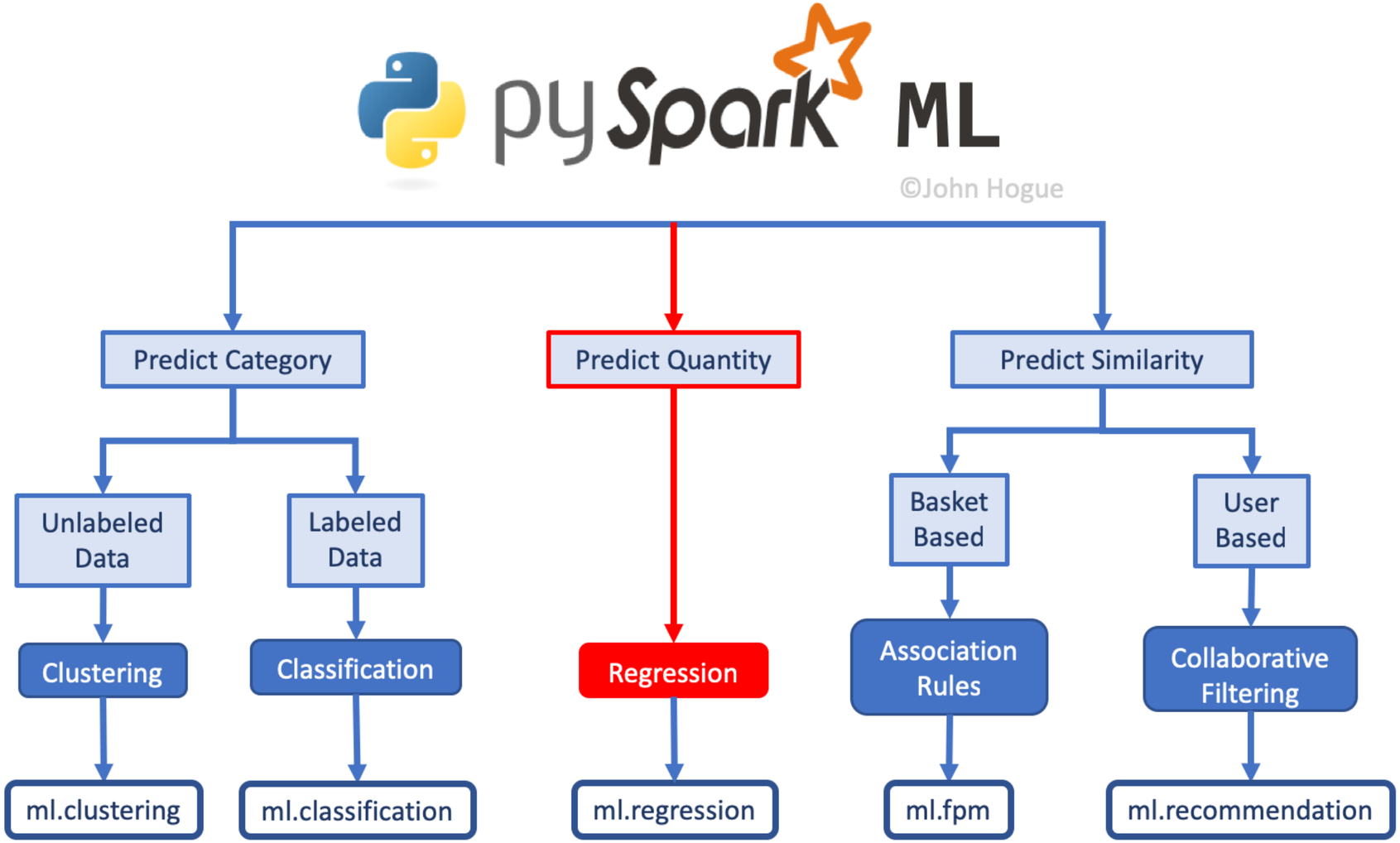
Spark ML Landscape



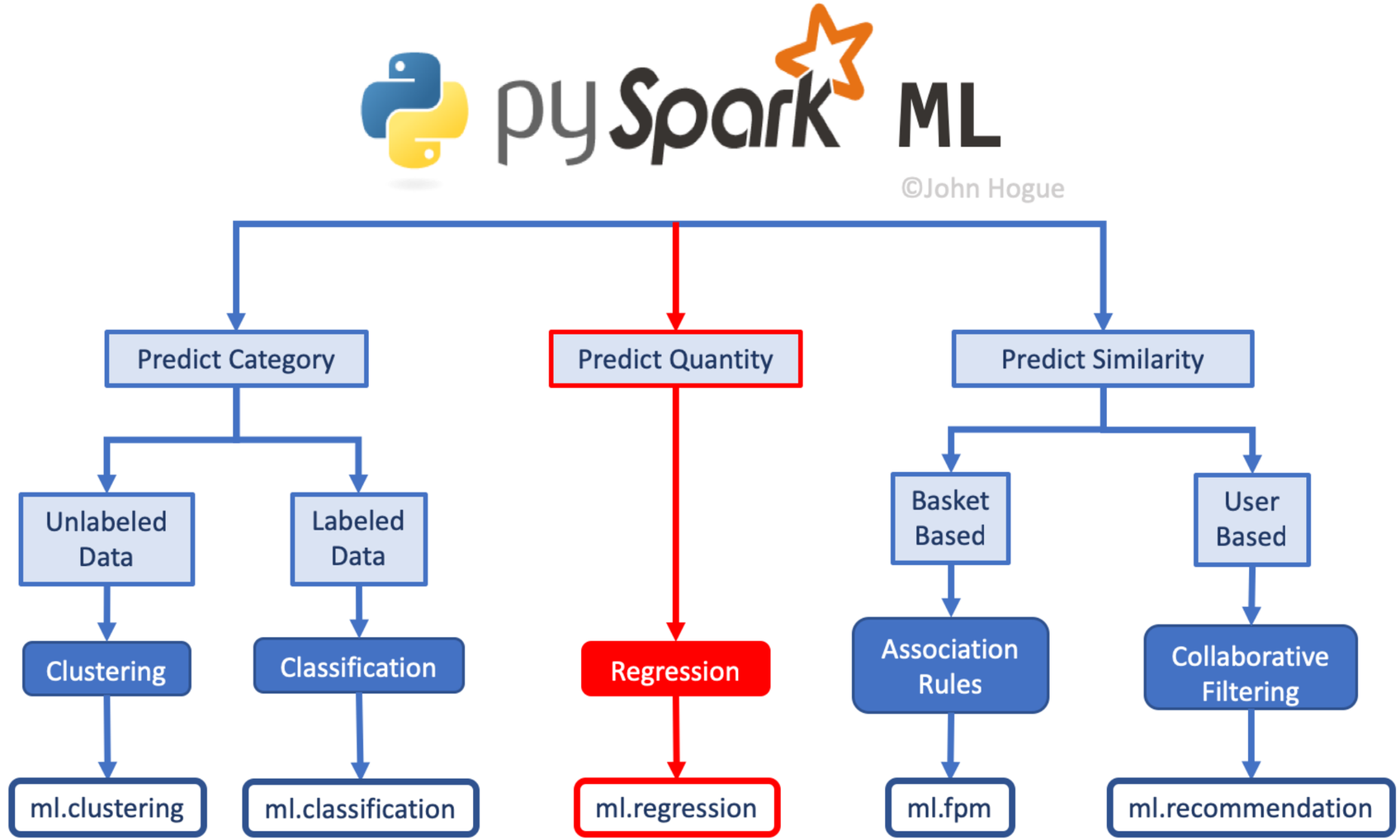
Spark ML Landscape



Spark ML Landscape



Spark ML Landscape



PySpark Regression Methods

Methods in `ml.regression` :

- `GeneralizedLinearRegression`
- `IsotonicRegression`
- `LinearRegression`
- `DecisionTreeRegression`
- `GBTRegression`
- `RandomForestRegression`

PySpark Regression Methods

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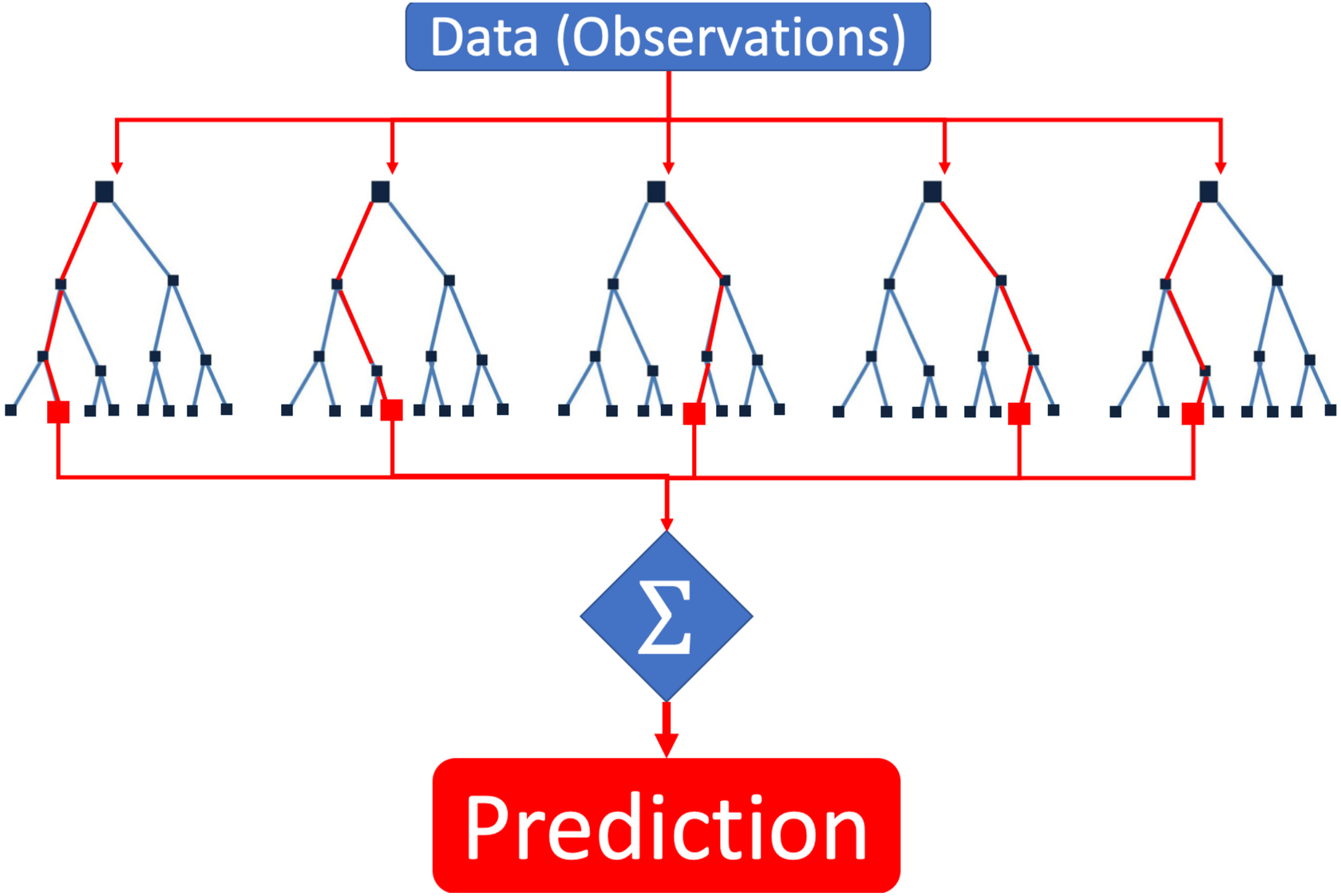
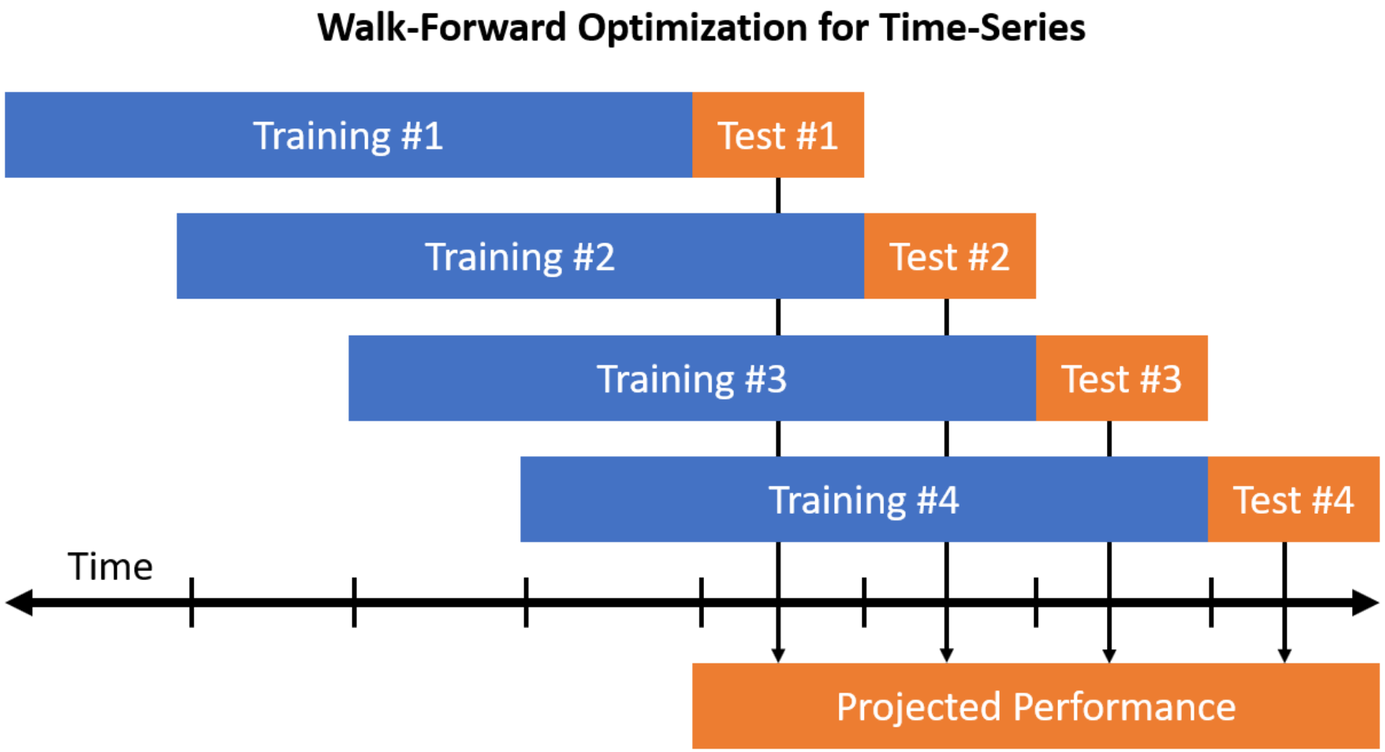

Data (Observations)
Σ
Prediction

Test and Train Splits for Time Series



https://www.kaggle.com/c/santander-value-prediction-challenge/discussion/61408

Test and Train Splits for Time Series

```
# Create variables for max and min dates in our dataset
max_date = df.agg({'OFFMKTDATE': 'max'}).collect()[0][0]
min_date = df.agg({'OFFMKTDATE': 'min'}).collect()[0][0]
```

```
# Find how many days our data spans
from pyspark.sql.functions import datediff
range_in_days = datediff(max_date, min_date)
```

```
# Find the date to split the dataset on
from pyspark.sql.functions import date_add
split_in_days = round(range_in_days * 0.8)
split_date = date_add(min_date, split_in_days)
```

```
# Split the data into 80% train, 20% test
train_df = df.where(df['OFFMKTDATE'] < split_date)
test_df = df.where(df['OFFMKTDATE'] >= split_date)\
  .where(df['LISTDATE'] >= split_date)
```

Time to practice!

FEATURE ENGINEERING WITH PYSPARK

Preparing for Random Forest Regression

FEATURE ENGINEERING WITH PYSPARK

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Assumptions Needed for Features

Random Forest Regression

- Skewed/Non Normal Data? OK
- Unscaled? OK
- Missing Data? OK
- Categorical Data? OK

Appended Features

Economic

- 30 Year Mortgage Rates

Governmental

- Median Home Price for City
- Home Age Percentages for City
- Home Size Percentages for City

Social

- Walk Score
- Bike Score

Seasonal

- Bank Holidays

Engineered Features

Temporal Features

- Limited value with one year of data
- Holiday Weeks

Rates, Ratios, Sums

- Business Context
- Personal Context

Expanded Features

- Non-Free Form Text Columns
- Need to Remove Low Observations

```
# What is shape of our data?
print((df.count(), len(df.columns)))
```

```
(5000, 126)
```

Dataframe Columns to Feature Vectors

```
from pyspark.ml.feature import VectorAssembler
```

```
# Replace Missing values
df = df.fillna(-1)
```

```
# Define the columns to be converted to vectors
features_cols = list(df.columns)
```

```
# Remove the dependent variable from the list
features_cols.remove('SALESCLOSEPRICE')
```

Dataframe Columns to Feature Vectors

```
# Create the vector assembler transformer
vec = VectorAssembler(inputCols=features_cols, outputCol='features')
# Apply the vector transformer to data
df = vec.transform(df)
# Select only the feature vectors and the dependent variable
ml_ready_df = df.select(['SALESCLOSEPRICE', 'features'])
# Inspect Results
ml_ready_df.show(5)
```

```
+---------------+--------------------+
| SALESCLOSEPRICE|            features|
+---------------+--------------------+
|143000          |(125,[0,1,2,3,5,6...|
|190000          |(125,[0,1,2,3,5,6...|
|225000          |(125,[0,1,2,3,5,6...|
|265000          |(125,[0,1,2,3,4,5...|
|249900          |(125,[0,1,2,3,4,5...|
+---------------+--------------------+
only showing top 5 rows
```

We are now ready for machine learning!

FEATURE ENGINEERING WITH PYSPARK

Building a Model

FEATURE ENGINEERING WITH PYSPARK

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RandomForestRegressor

Basic Model Parameters

- `featuresCol="features"`
- `labelCol="label"`
- `predictionCol="prediction"`
- `seed=None`

Our Model Parameter values

- `featuresCol="features"`
- `labelCol="SALESCLOSEPRICE"`
- `predictionCol="Prediction_Price"`
- `seed=42`

Training a Random Forest

```
from pyspark.ml.regression import RandomForestRegressor
```

```
# Initialize model with columns to utilize
rf = RandomForestRegressor(featuresCol="features",
                           labelCol="SALESCLOSEPRICE",
                           predictionCol="Prediction_Price",
                           seed=42
                           )
```

```
# Train model
model = rf.fit(train_df)
```

Predicting with a Model

```
# Make predictions
predictions = model.transform(test_df)
```

```
# Inspect results
predictions.select("Prediction_Price", "SALESCLOSEPRICE").show(5)
```

```
+------------------+---------------+
|  Prediction_Price|SALESCLOSEPRICE|
+------------------+---------------+
|426029.55463222397|         415000|
| 708510.8806005502|         842500|
| 164275.7116183204|         161000|
| 208943.4143642175|         200000|
|217152.43272221283|         205000|
+------------------+---------------+
only showing top 5 rows
```

Evaluating a Model

```
from pyspark.ml.evaluation import RegressionEvaluator
```

```
# Select columns to compute test error
evaluator = RegressionEvaluator(labelCol="SALESCLOSEPRICE",
                                predictionCol="Prediction_Price")
```

```
# Create evaluation metrics
rmse = evaluator.evaluate(predictions, {evaluator.metricName: "rmse"})
r2 = evaluator.evaluate(predictions, {evaluator.metricName: "r2"})
```

```
# Print Model Metrics
print('RMSE: ' + str(rmse))
print('R^2: ' + str(r2))
```

```
RMSE: 22898.84041072095
R^2: 0.9666594402208077
```

Let's model some data!

FEATURE ENGINEERING WITH PYSPARK

Interpreting, Saving & Loading Models

FEATURE ENGINEERING WITH PYSPARK

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Interpreting a Model

```
import pandas as pd
```

```
# Convert feature importances to a pandas column
fi_df = pd.DataFrame(model.featureImportances.toArray(),
                     columns=['importance'])
```

```
# Convert list of feature names to pandas column
fi_df['feature'] = pd.Series(feature_cols)
```

```
# Sort the data based on feature importance
fi_df.sort_values(by=['importance'], ascending=False, inplace=True)
```

Interpreting a Model

```
# Interpret results
model_df.head(9)
```

```
|          feature         |importance|
|--------------------------|----------|
| LISTPRICE                | 0.312101 |
| ORIGINALLISTPRICE        | 0.202142 |
| LIVINGAREA               | 0.124239 |
| SQFT_TOTAL               | 0.081260 |
| LISTING_TO_MEDIAN_RATIO  | 0.075086 |
| TAXES                    | 0.048452 |
| SQFTABOVEGROUND          | 0.045859 |
| BATHSTOTAL               | 0.034397 |
| LISTING_PRICE_PER_SQFT   | 0.018253 |
```

Saving & Loading Models

```
# Save model
model.save('rfr_real_estate_model')
```

```
from pyspark.ml.regression import RandomForestRegressionModel


# Load model from
model2 = RandomForestRegressionModel.load('rfr_real_estate_model')
```

On to your last set of exercises!

FEATURE ENGINEERING WITH PYSPARK

Final Thoughts

FEATURE ENGINEERING WITH PYSPARK

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Lead Data Scientist

What you learned!

- Inspecting visually & statistically
- Dropping rows and columns
- Scaling and adjusting data
- Handling missing values
- Joining external datasets
- Generating features
- Extracting variables from messy fields
- Binning, bucketing and encoding
- Training and evaluating a model
- Interpreting model results

Time to learn something new!

FEATURE ENGINEERING WITH PYSPARK