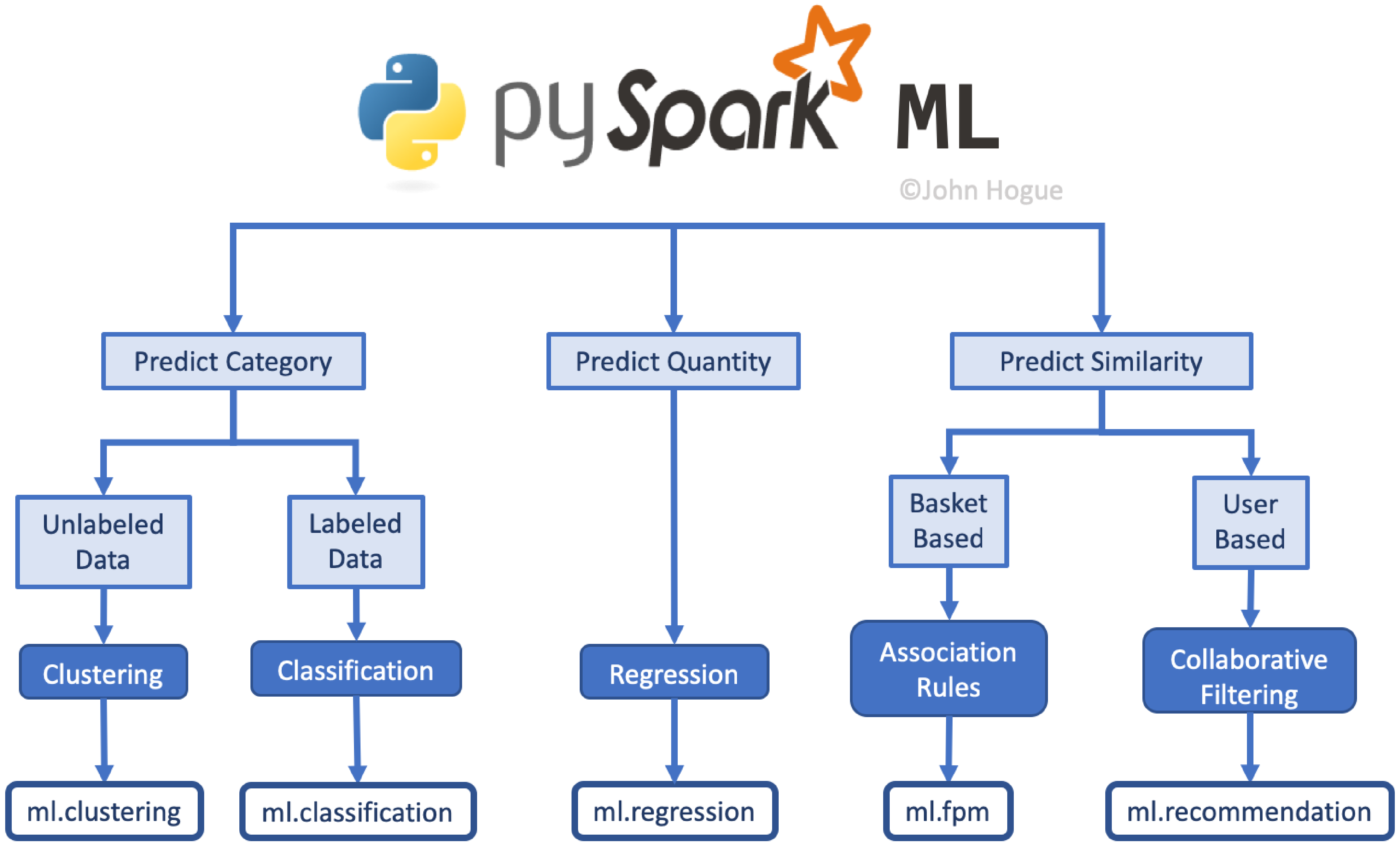
Choosing the Algorithm

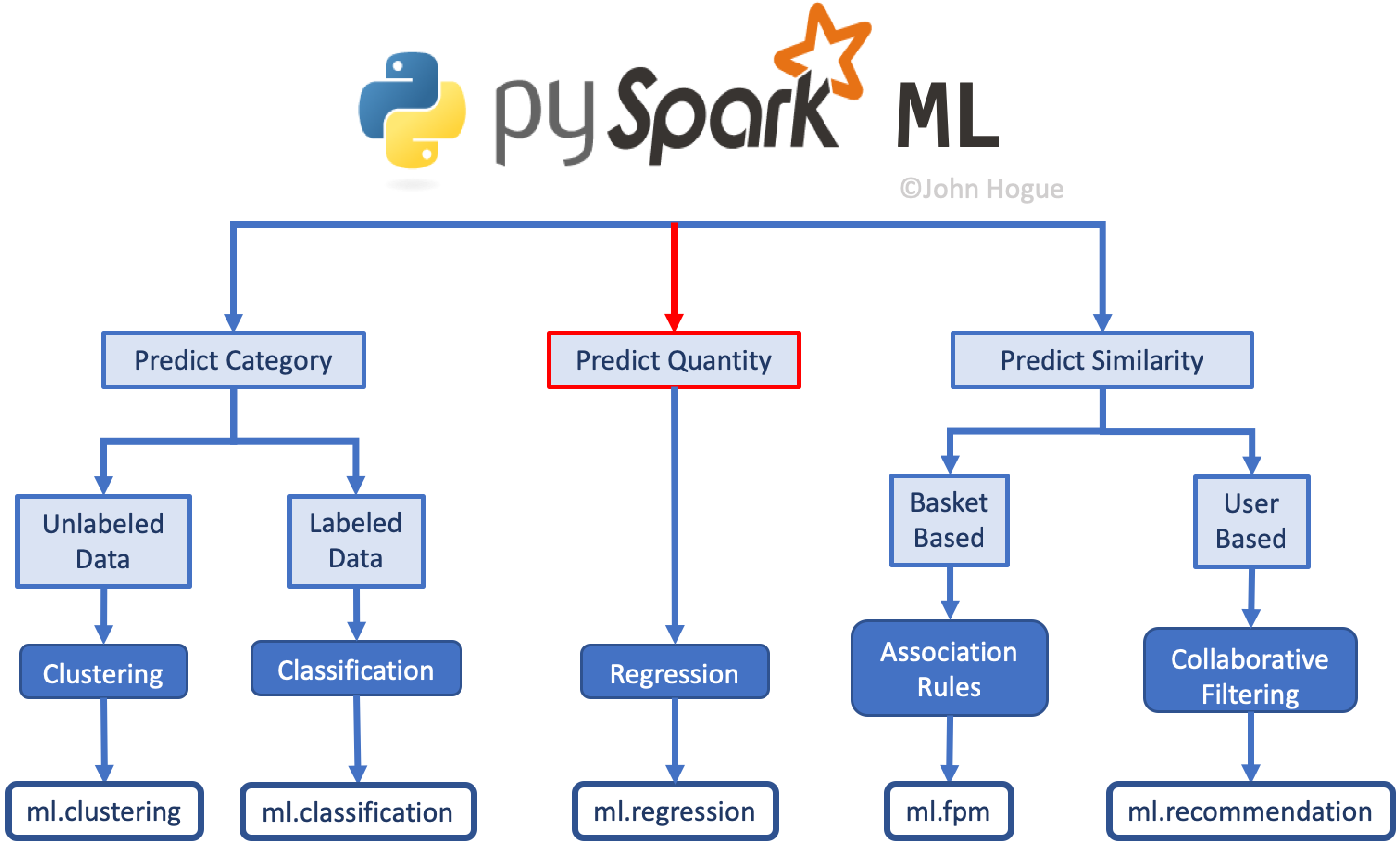
FEATURE ENGINEERING WITH PYSPARK

John Hogue
Lead Data Scientist, General Mills

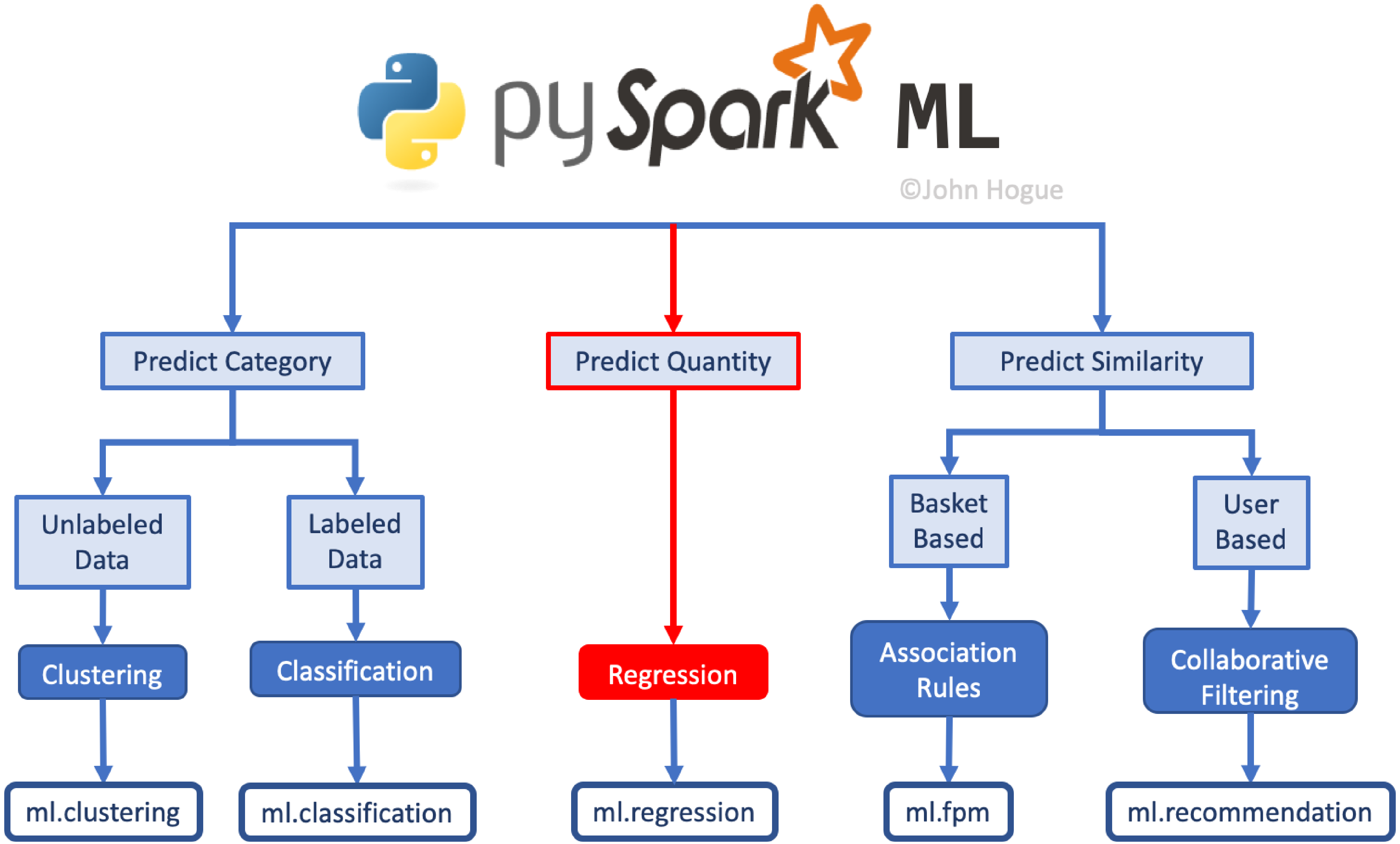
Spark ML Landscape



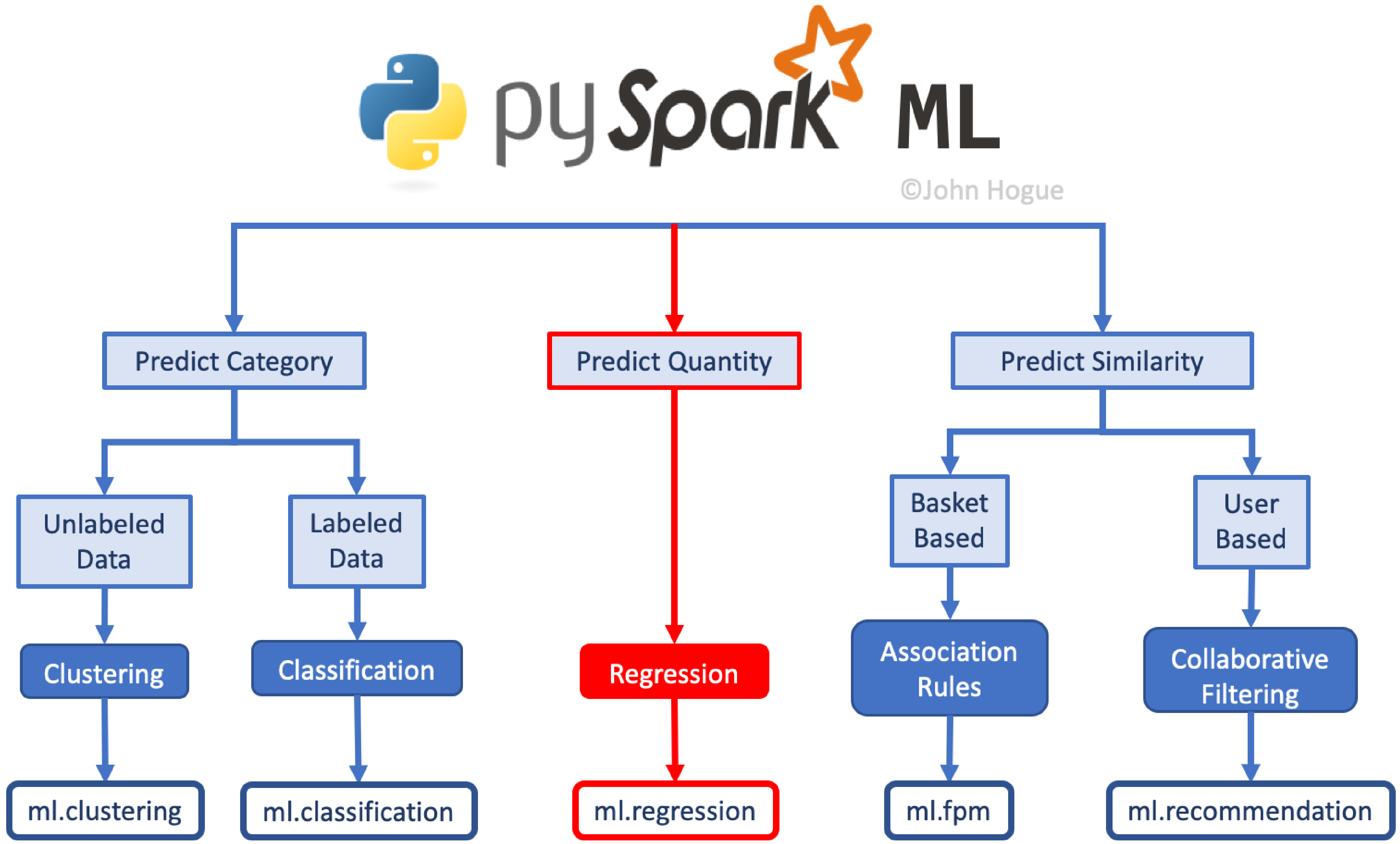
Spark ML Landscape



Spark ML Landscape



Spark ML Landscape



PySpark Regression Methods

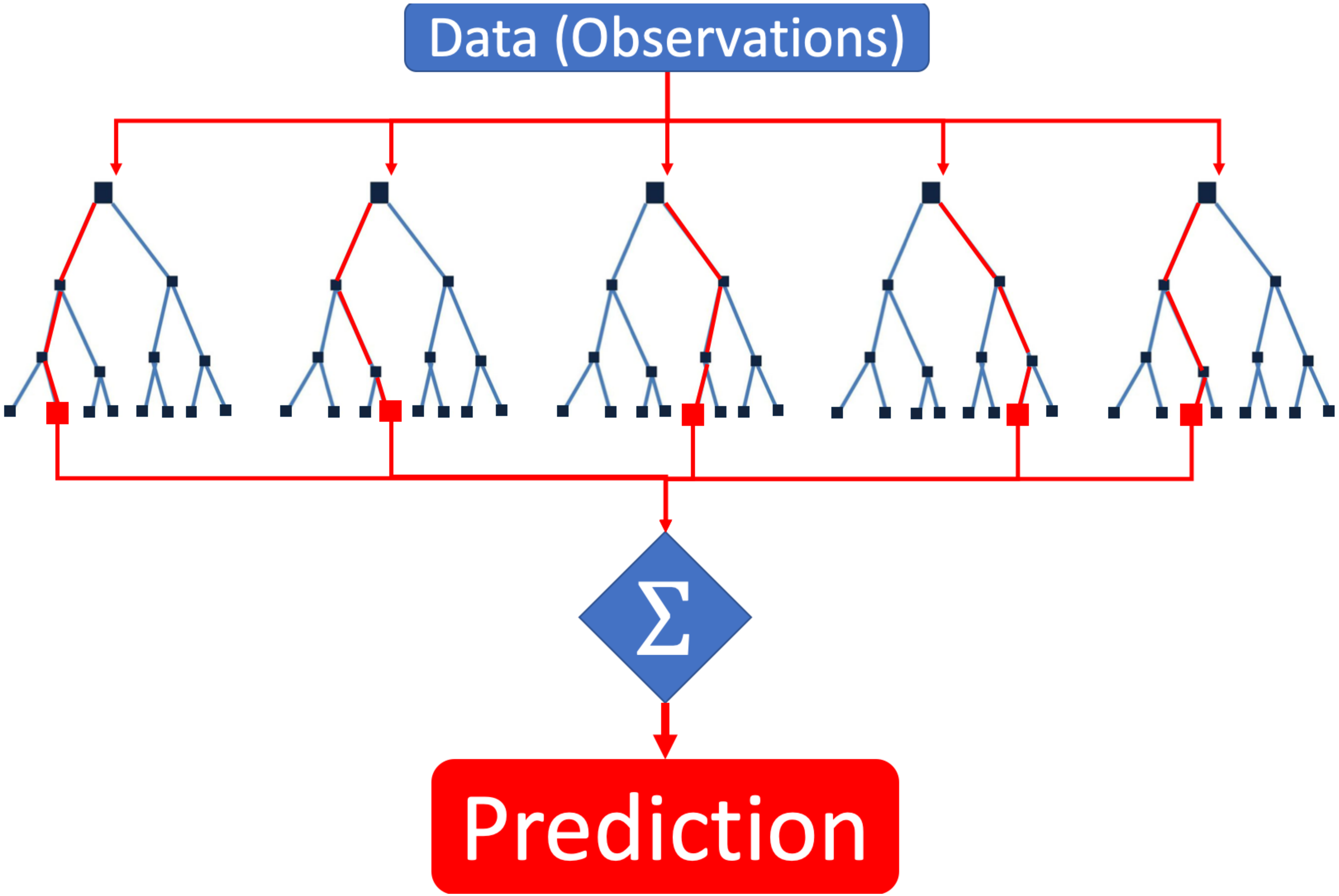
Methods in `ml.regression` :

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

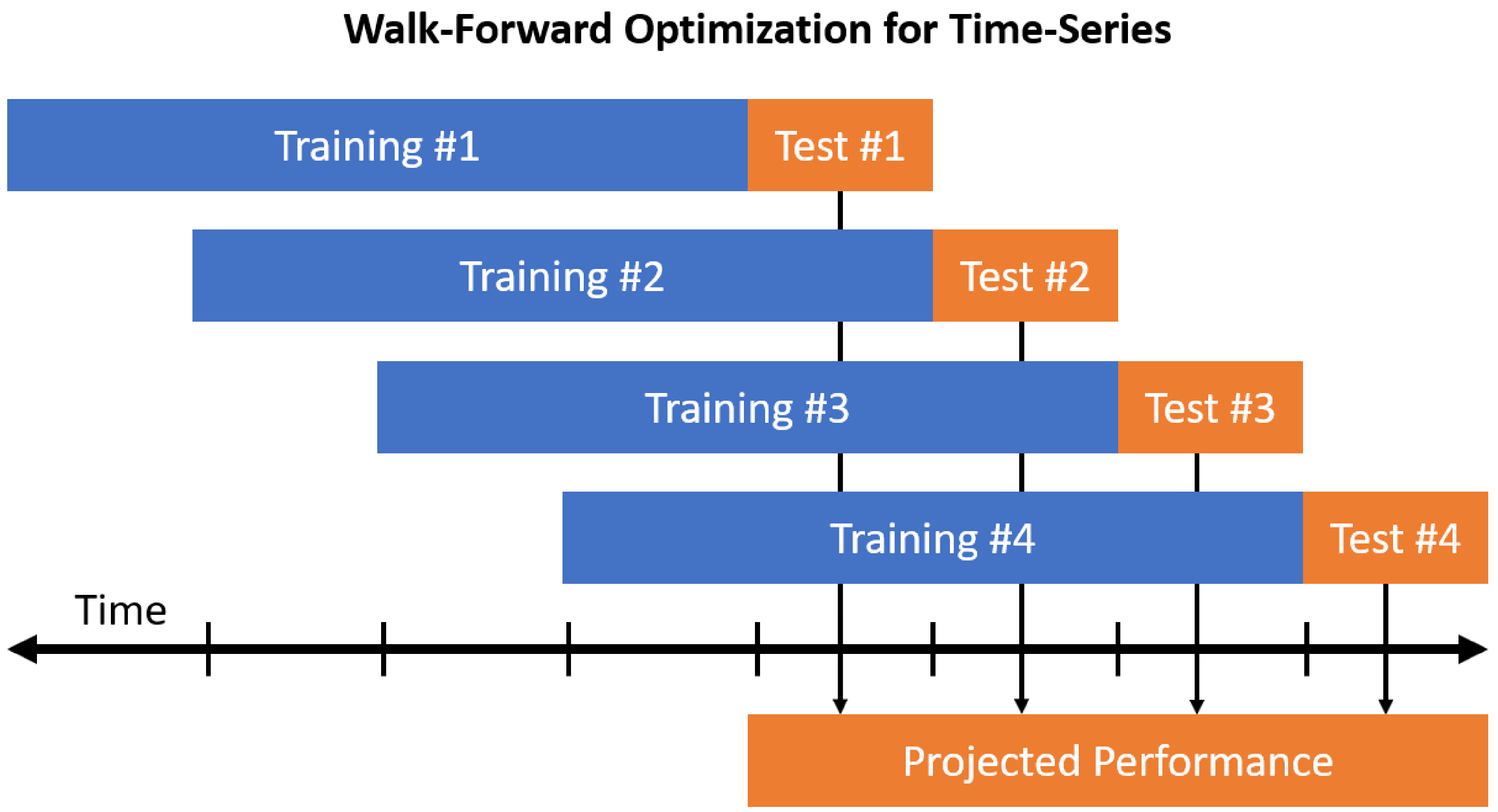
PySpark Regression Methods

Methods in `ml.regression`:

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


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

John Hogue
Lead Data Scientist, General Mills

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

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

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

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

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

Dataframe Columns to Feature Vectors

```python
# 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

John Hogue
Lead Data Scientist, General Mills

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

John Hogue
Lead Data Scientist, General Mills

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

John Hogue
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