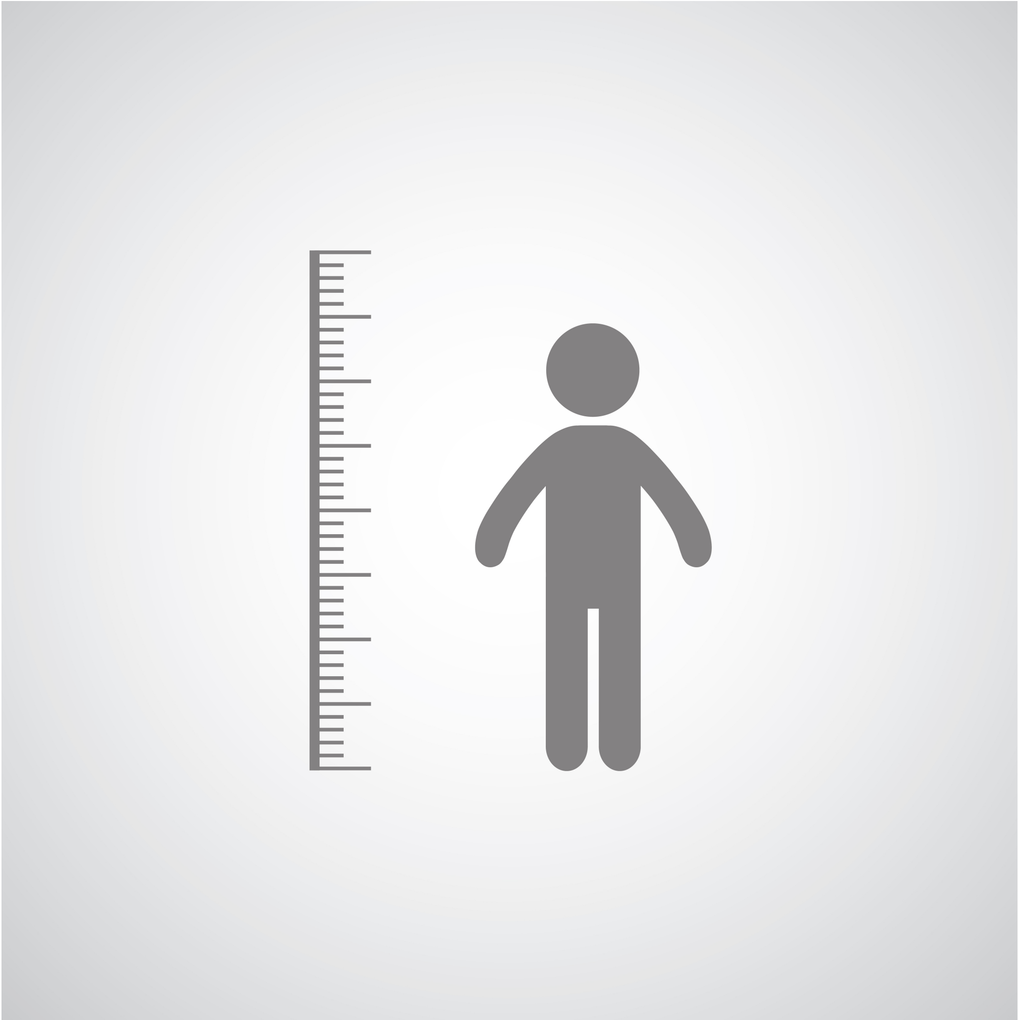
EXTREME GRADIENT BOOSTING WITH XGBOOST

Regression review

Sergey Fogelson
VP of Analytics, Viacom

Regression basics

- Outcome is real-valued



Common regression metrics

- Root mean squared error (RMSE)
- Mean absolute error (MAE)

Computing RMSE

Actual	Predicted
10	20
3	8
6	1

Computing RMSE

Actual	Predicted	Error
10	20	-10
3	8	-5
6	1	5

Computing RMSE

Actual	Predicted	Error	Squared Error
10	20	-10	100
3	8	-5	25
6	1	5	25

- Total Squared Error: 150
- Mean Squared Error: 50
- Root Mean Squared Error: 7.07

Computing MAE

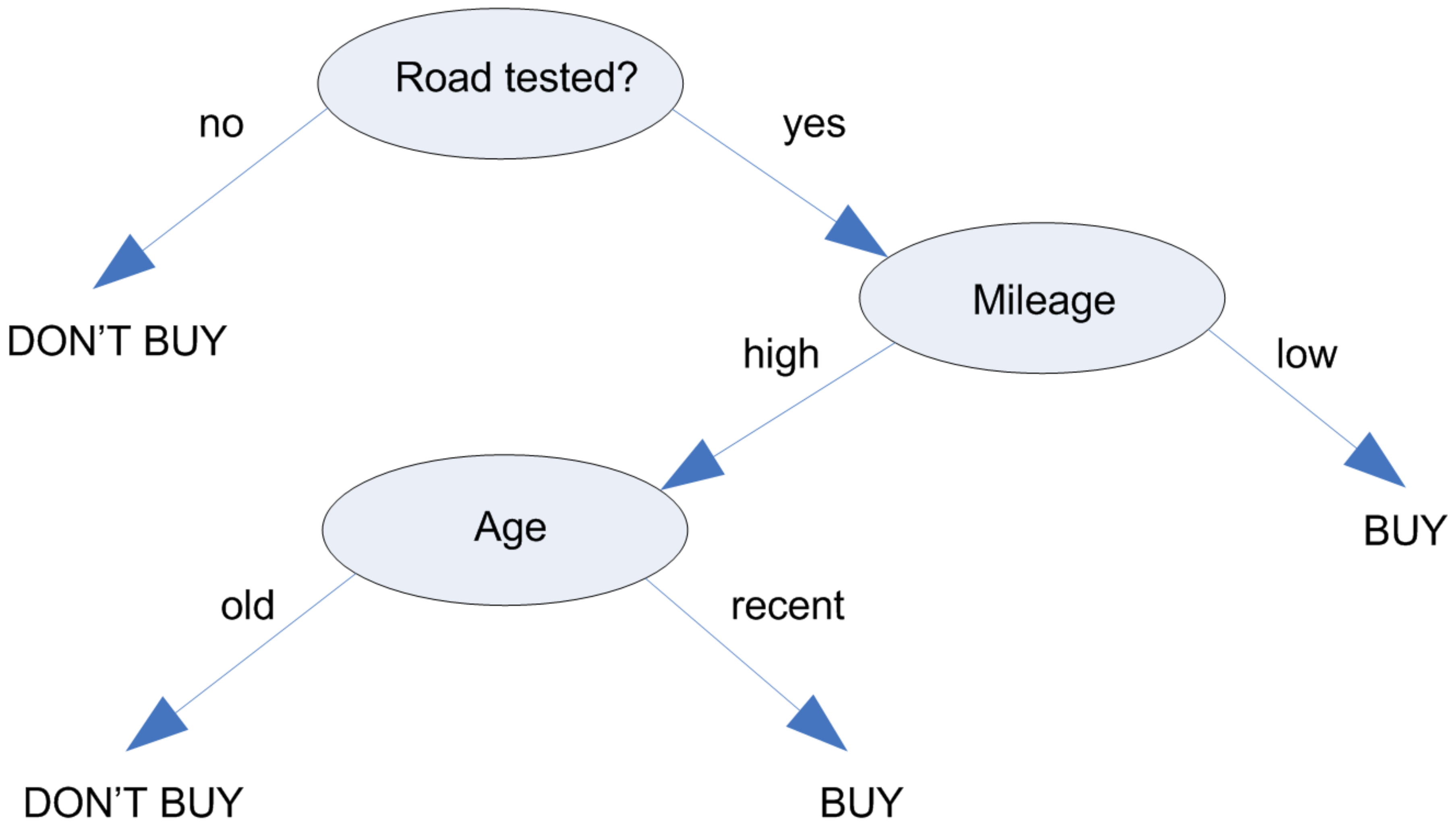
Actual	Predicted	Error
10	20	-10
3	8	-5
6	1	5

- Total Absolute Error: 20
- Mean Absolute Error: 6.67

Common regression algorithms

- Linear regression
- Decision trees

Algorithms for both regression and classification



[1] https://www.ibm.com/support/knowledgecenter/en/SS3RA7_15.0.0/com.ibm.spss.modeler.help/nodes_treebuilding.htm

EXTREME GRADIENT BOOSTING WITH XGBOOST

Let's practice!

EXTREME GRADIENT BOOSTING WITH XGBOOST

Objective (loss) functions and base learners

Sergey Fogelson
VP of Analytics, Viacom

Objective Functions and Why We Use Them

- Quantifies how far off a prediction is from the actual result
- Measures the difference between estimated and true values for some collection of data
- Goal: Find the model that yields the minimum value of the loss function

Common Loss Functions and XGBoost

- Loss function names in xgboost:
    - reg:linear - use for regression problems
    - reg:logistic - use for classification problems when you want just decision, not probability
    - binary:logistic - use when you want probability rather than just decision

Base Learners and Why We Need Them

- XGBoost involves creating a meta-model that is composed of many individual models that combine to give a final prediction
- Individual models = base learners
- Want base learners that when combined create final prediction that is **non-linear**
- Each base learner should be good at distinguishing or predicting different parts of the dataset
- Two kinds of base learners: tree and linear

Trees as Base Learners example: Scikit-learn API

```
In [1]: import xgboost as xgb

In [2]: import pandas as pd

In [3]: import numpy as np

In [4]: from sklearn.model_selection import train_test_split

In [5]: boston_data = pd.read_csv("boston_housing.csv")

In [6]: X, y = boston_data.iloc[:,:-1],boston_data.iloc[:,-1]

In [7]: X_train, X_test, y_train, y_test= train_test_split(X, y,
        test_size=0.2, random_state=123)

In [8]: xg_reg = xgb.XGBRegressor(objective='reg:linear',
        n_estimators=10, seed=123)

In [9]: xg_reg.fit(X_train, y_train)

In [10]: preds = xg_reg.predict(X_test)
```

Trees as base learners example: Scikit-learn API

```
In [11]: rmse = np.sqrt(mean_squared_error(y_test,preds))

In [12]: print("RMSE: %f" % (rmse))
RMSE: 129043.2314
```

Linear Base Learners Example: Learning API Only

```
In [1]: import xgboost as xgb

In [2]: import pandas as pd

In [3]: import numpy as np

In [4]: from sklearn.model_selection import train_test_split

In [5]: boston_data = pd.read_csv("boston_housing.csv")

In [6]: X, y = boston_data.iloc[:,:-1],boston_data.iloc[:,-1]

In [7]: X_train, X_test, y_train, y_test= train_test_split(X, y,
        test_size=0.2, random_state=123)

In [8]: DM_train = xgb.DMatrix(data=X_train,label=y_train)

In [9]: DM_test =  xgb.DMatrix(data=X_test,label=y_test)

In [10]: params = {"booster":"gblinear","objective":"reg:linear"}

In [11]: xg_reg = xgb.train(params = params, dtrain=DM_train,
         num_boost_round=10)

In [12]: preds = xg_reg.predict(DM_test)
```

Linear base learners example: Learning API only

```
In [13]: rmse = np.sqrt(mean_squared_error(y_test,preds))

In [14]: print("RMSE: %f" % (rmse))
RMSE: 124326.24465
```

EXTREME GRADIENT BOOSTING WITH XGBOOST

Let's get to work!

EXTREME GRADIENT BOOSTING WITH XGBOOST

Regularization and base learners in XGBoost

Sergey Fogelson
VP of Analytics, Viacom

Regularization in XGBoost

- Regularization is a control on model complexity
- Want models that are both accurate and as simple as possible
- Regularization parameters in XGBoost:
  - gamma - minimum loss reduction allowed for a split to occur
  - alpha - l1 regularization on leaf weights, larger values mean more regularization
  - lambda - l2 regularization on leaf weights

L1 Regularization in XGBoost example

```
In [1]: import xgboost as xgb
In [2]: import pandas as pd
In [3]: boston_data = pd.read_csv("boston_data.csv")
In [4]: X,y = boston_data.iloc[:,:-1],boston_data.iloc[:,-1]

In [5]: boston_dmatrix = xgb.DMatrix(data=X,label=y)
In [6]: params={"objective":"reg:linear","max_depth":4}

In [7]: l1_params = [1,10,100]
In [8]: rmses_l1=[]

In [9]: for reg in l1_params:
   ...:     params["alpha"] = reg
   ...:     cv_results = xgb.cv(dtrain=boston_dmatrix,
   ...:     params=params,nfold=4,
   ...:     num_boost_round=10,metrics="rmse",as_pandas=True,seed=123)
   ...:     rmses_l1.append(cv_results["test-rmse-mean"] \
            .tail(1).values[0])

In [10]: print("Best rmse as a function of l1:")
In [11]: print(pd.DataFrame(list(zip(l1_params,rmses_l1)),
         columns=["l1","rmse"]))
Best rmse as a function of l1:
        l1          rmse
    0    1  69572.517742
    1   10  73721.967141
    2  100  82312.312413
```

Base Learners in XGBoost

- Linear Base Learner:
  - Sum of linear terms
  - Boosted model is weighted sum of linear models (thus is itself linear)
  - Rarely used
- Tree Base Learner:
  - Decision tree
  - Boosted model is weighted sum of decision trees (nonlinear)
  - Almost exclusively used in XGBoost

Creating DataFrames from multiple equal-length lists

- `pd.DataFrame(list(zip(list1,list2)),columns=["list1","list2"]))`
- `zip` creates a `generator` of parallel values:
  - `zip([1,2,3],["a","b""c"])` = `[1,"a"],[2,"b"],[3,"c"]`
  - `generators` need to be completely instantiated before they can be used in `DataFrame` objects
- `list()` instantiates the full generator and passing that into the `DataFrame` converts the whole expression

EXTREME GRADIENT BOOSTING WITH XGBOOST

Let's practice!