Machine Learning Basics

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Standard Model of ML running:

1. Inheriting ML Code
2. Modify
3. Create your training sample
4. Get total nonsense
5. Google for answers
6. Eureka moment
7. Try it

Repeat from step 5 until succeed

ML running basics

ML running basics

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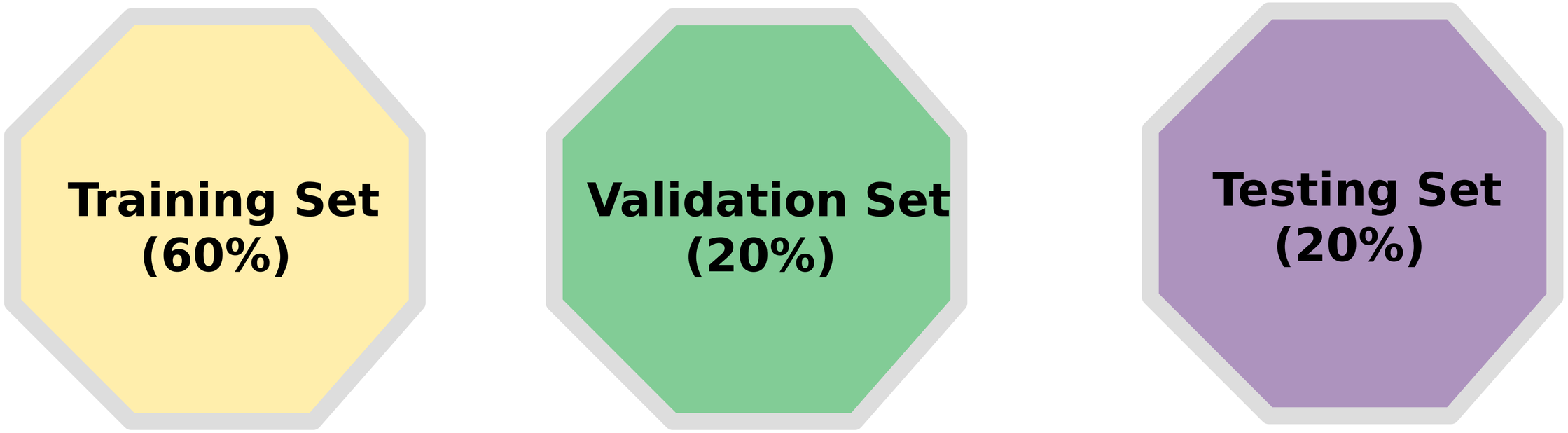

To train the models

To prevent overfitting

To determine accuracy

Each ML model has multiple parameters:
Run with various sets then find the best

ML running basics

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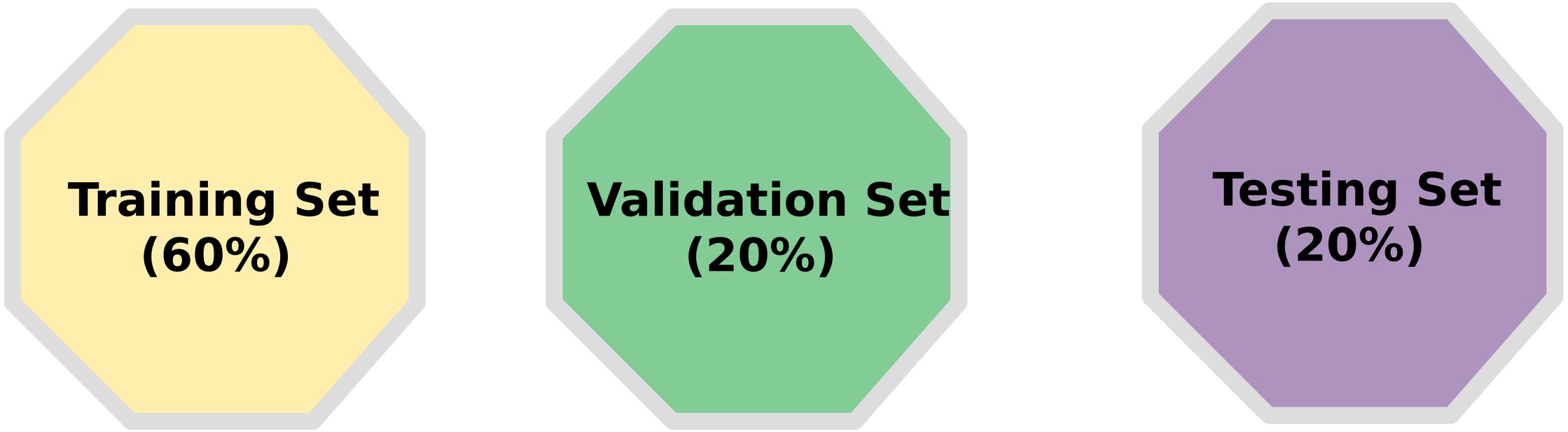

To train the models

To prevent overfitting

To determine accuracy

Each ML model has multiple parameters:
Run with various sets then find the best
FOR YOU

Classification in ML

Classification in ML

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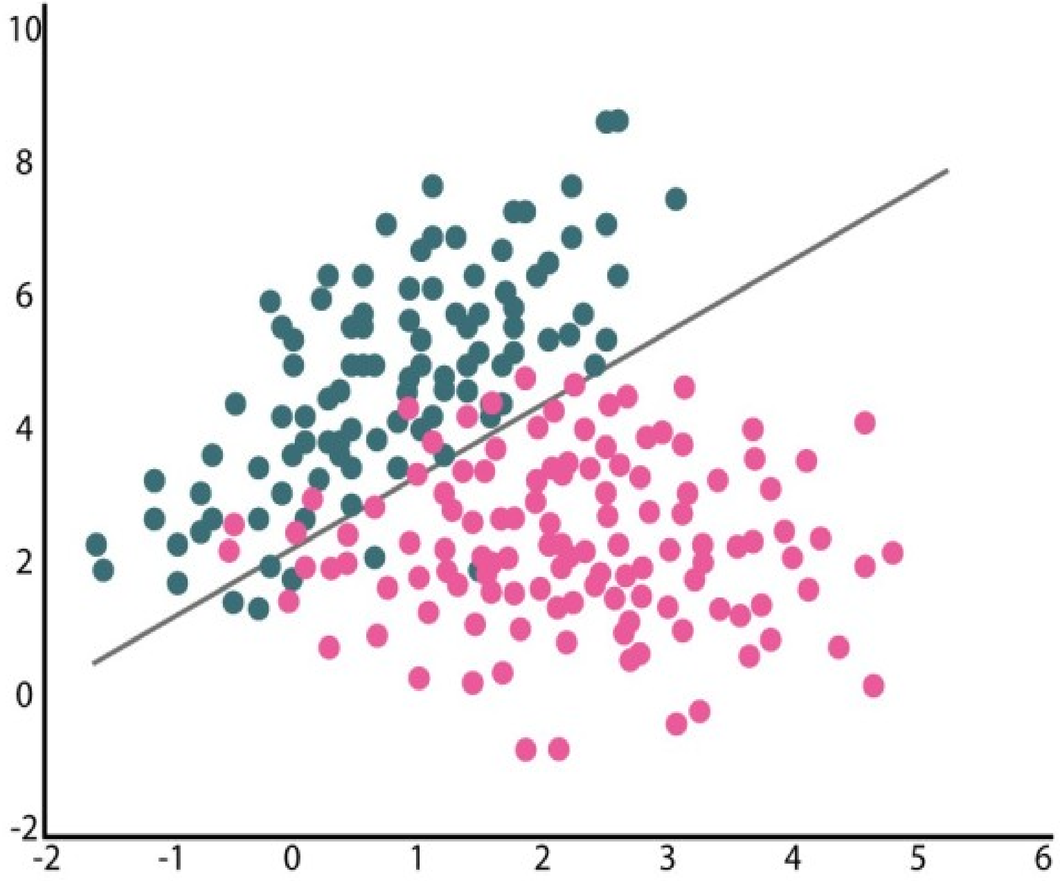
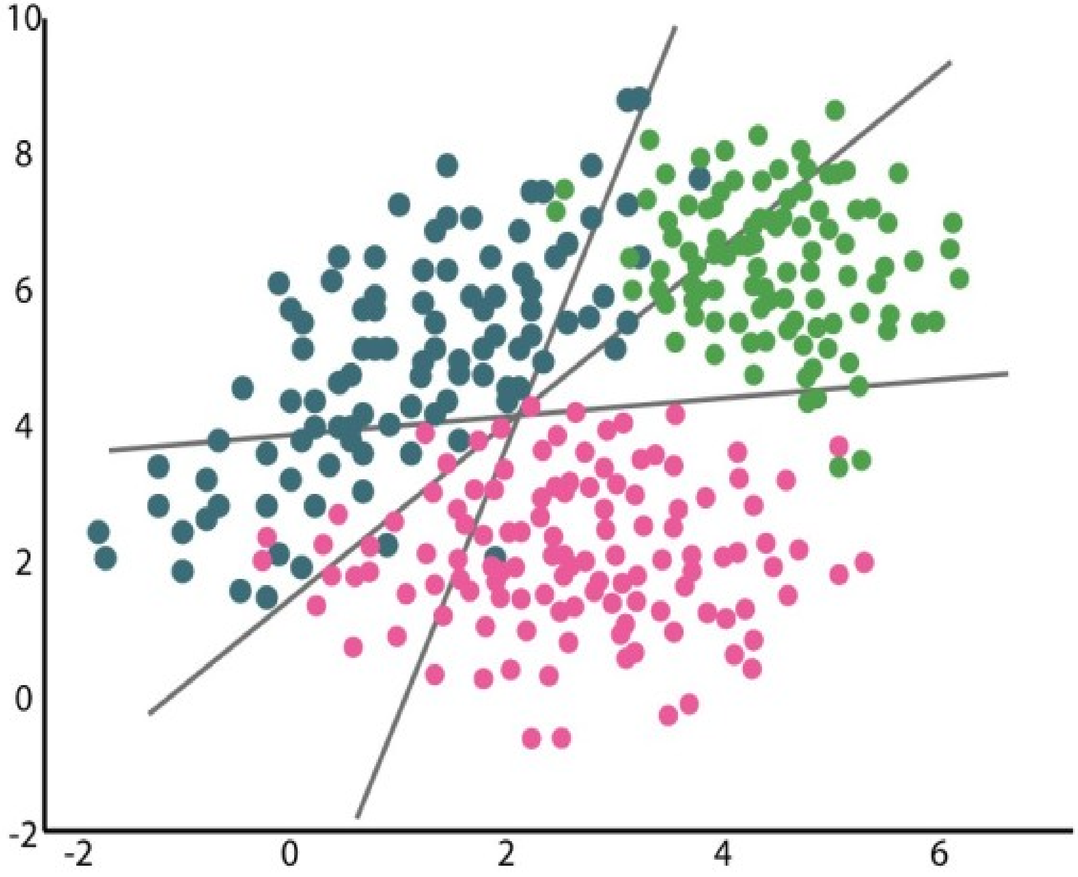
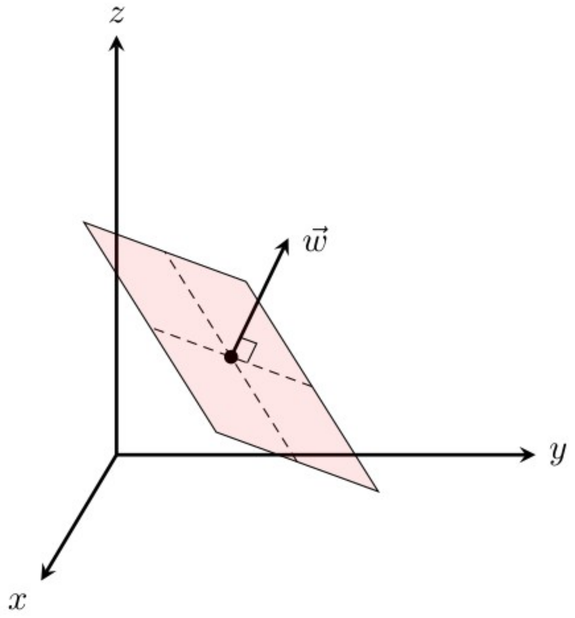
Binary classification

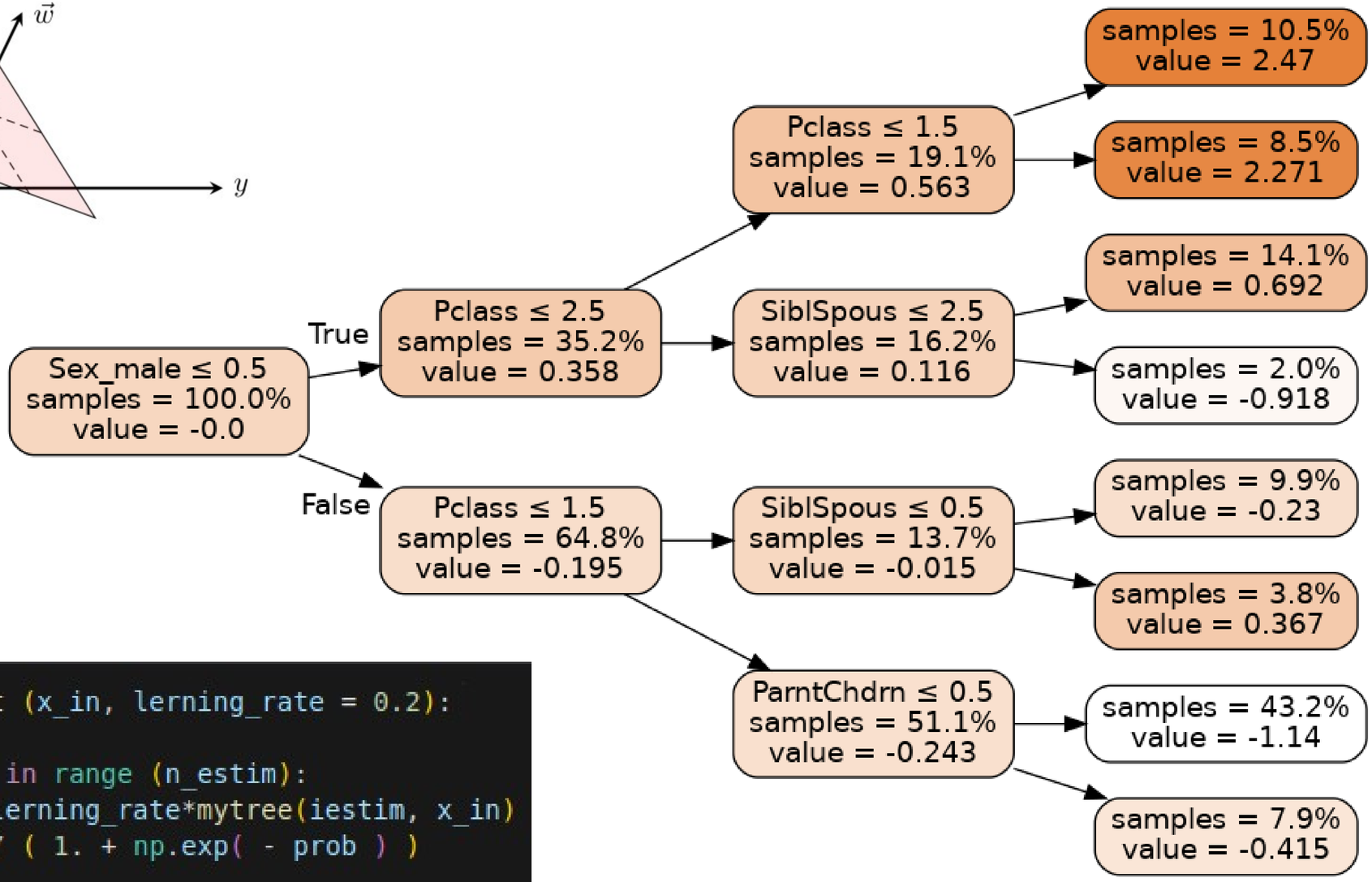


Multi-class classification



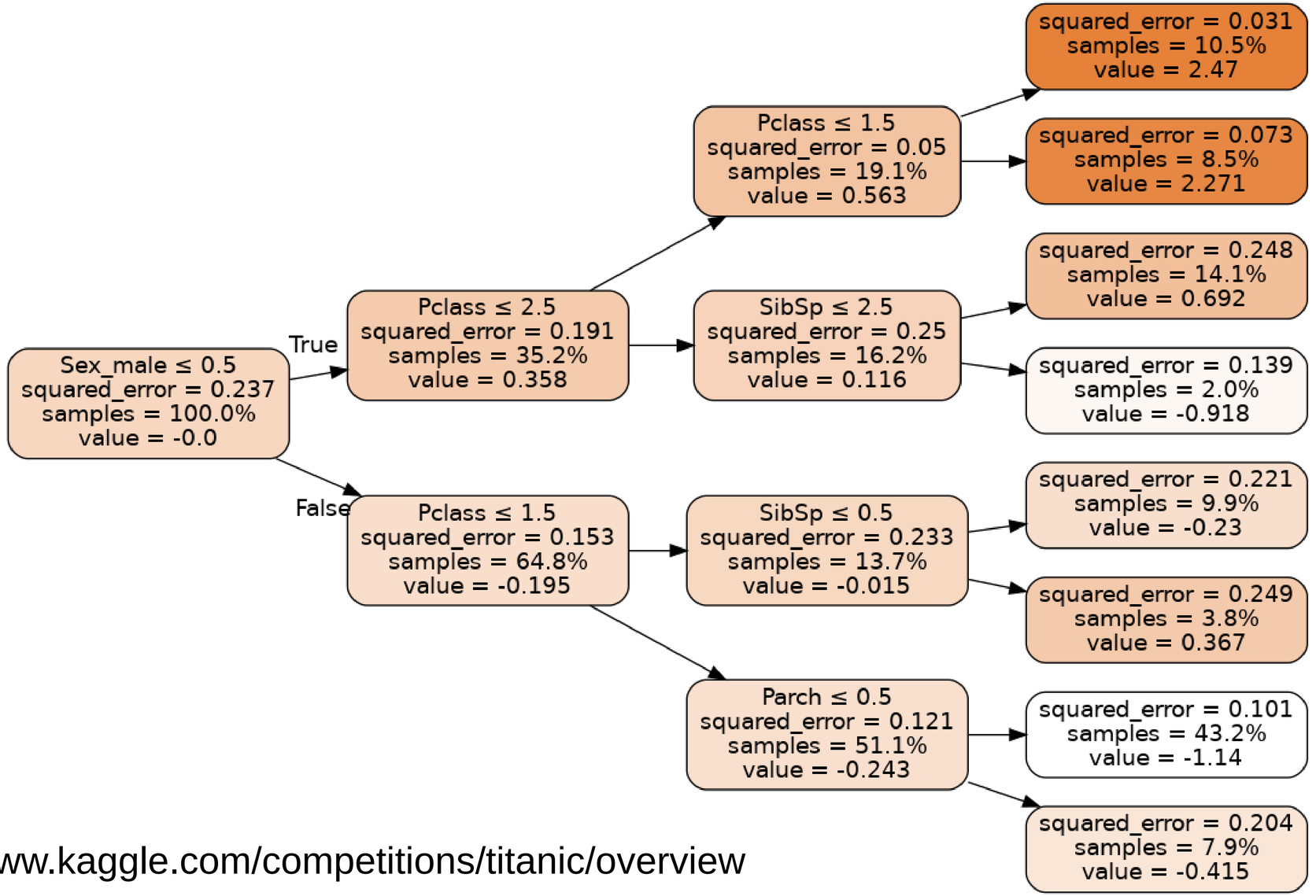
Example






```python
def mygradboost (x_in, lerning_rate = 0.2):
    prob = 0
    for iestim in range (n_estim):
        prob+=lerning_rate*mytree(iestim, x_in)
    return 1. / ( 1. + np.exp( - prob ) )
```

Example



https://www.kaggle.com/competitions/titanic/overview

Quality metrics

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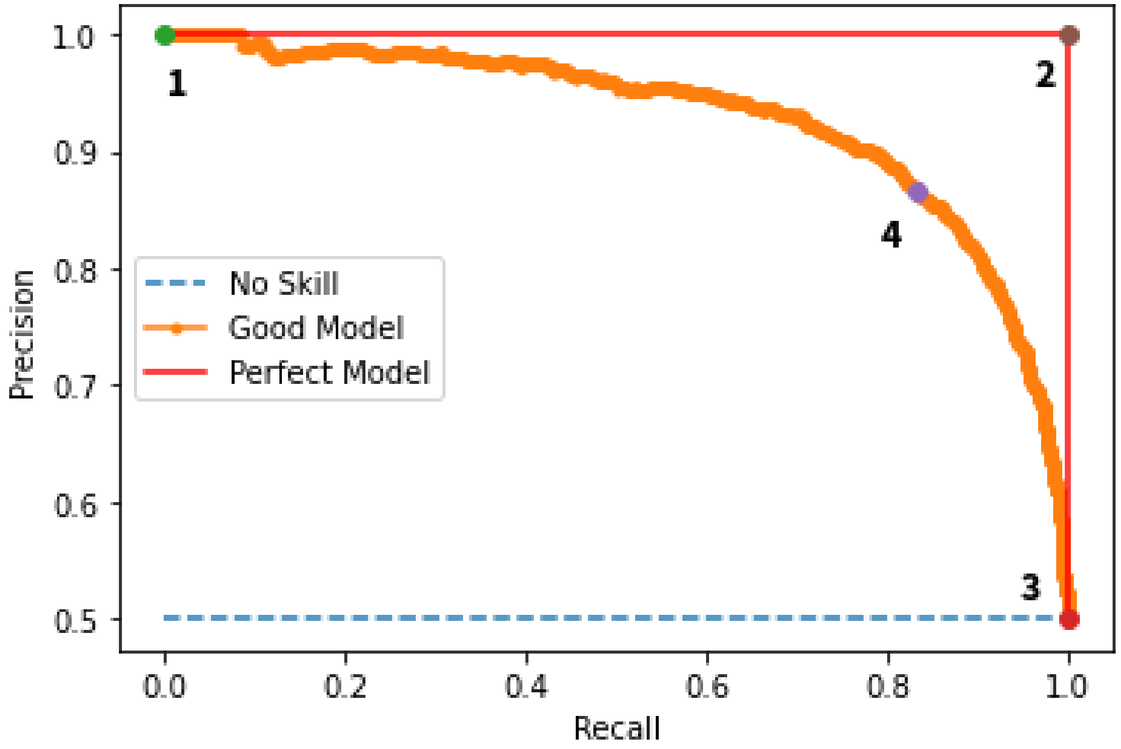
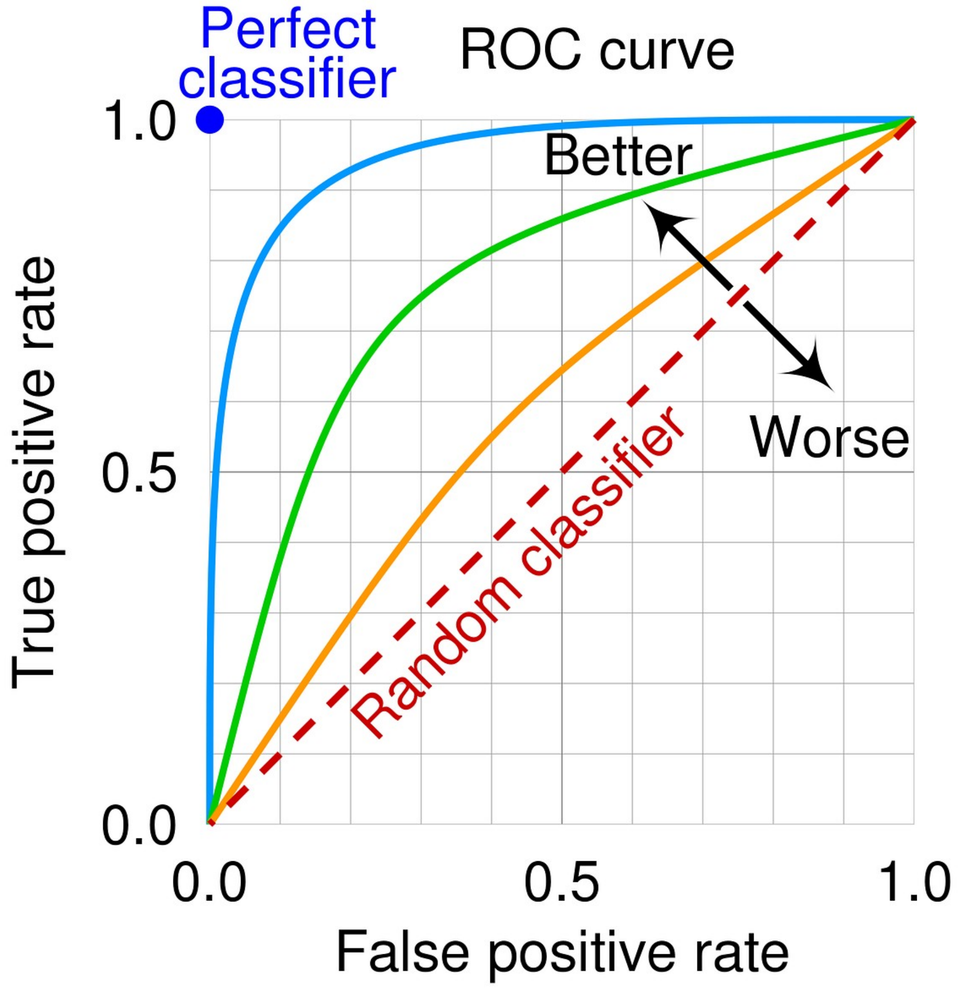
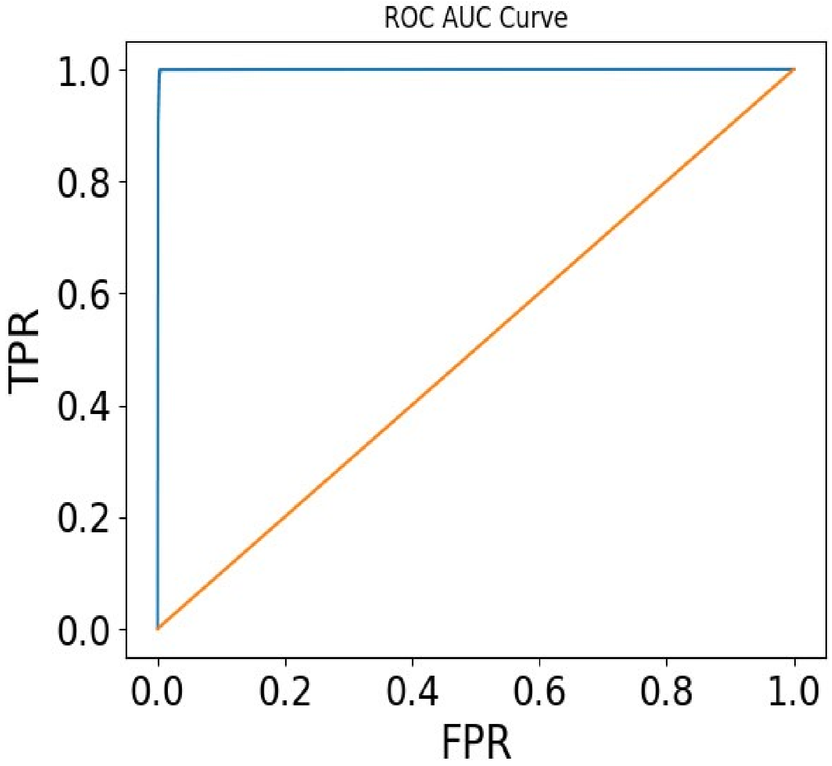
$$precision = \frac{TP}{TP + FP} \qquad recall = \frac{TP}{TP + FN}$$

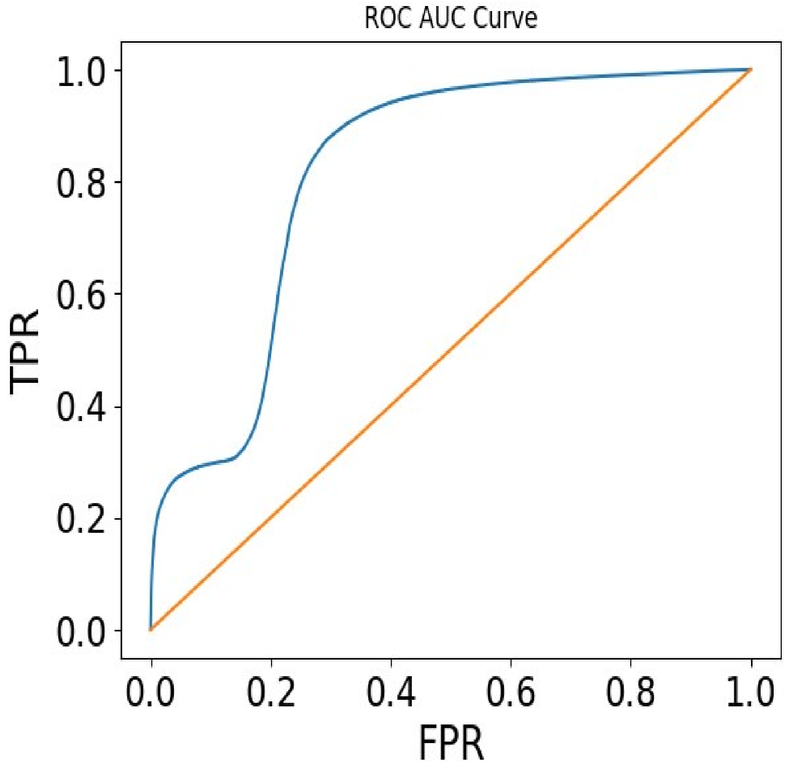


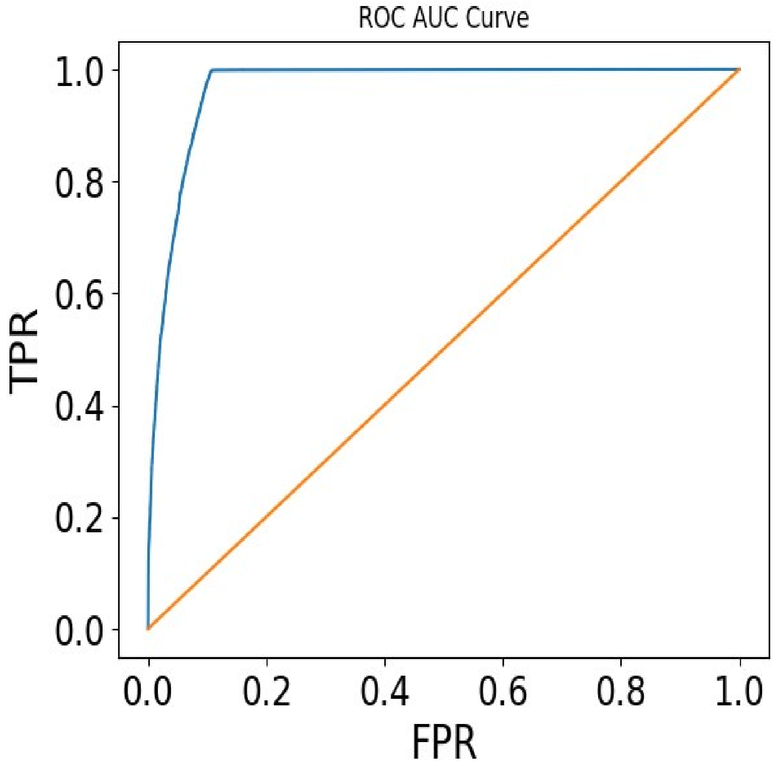
$$TPR = \frac{TP}{TP + FN} \qquad FPR = \frac{FP}{FP + TN}$$



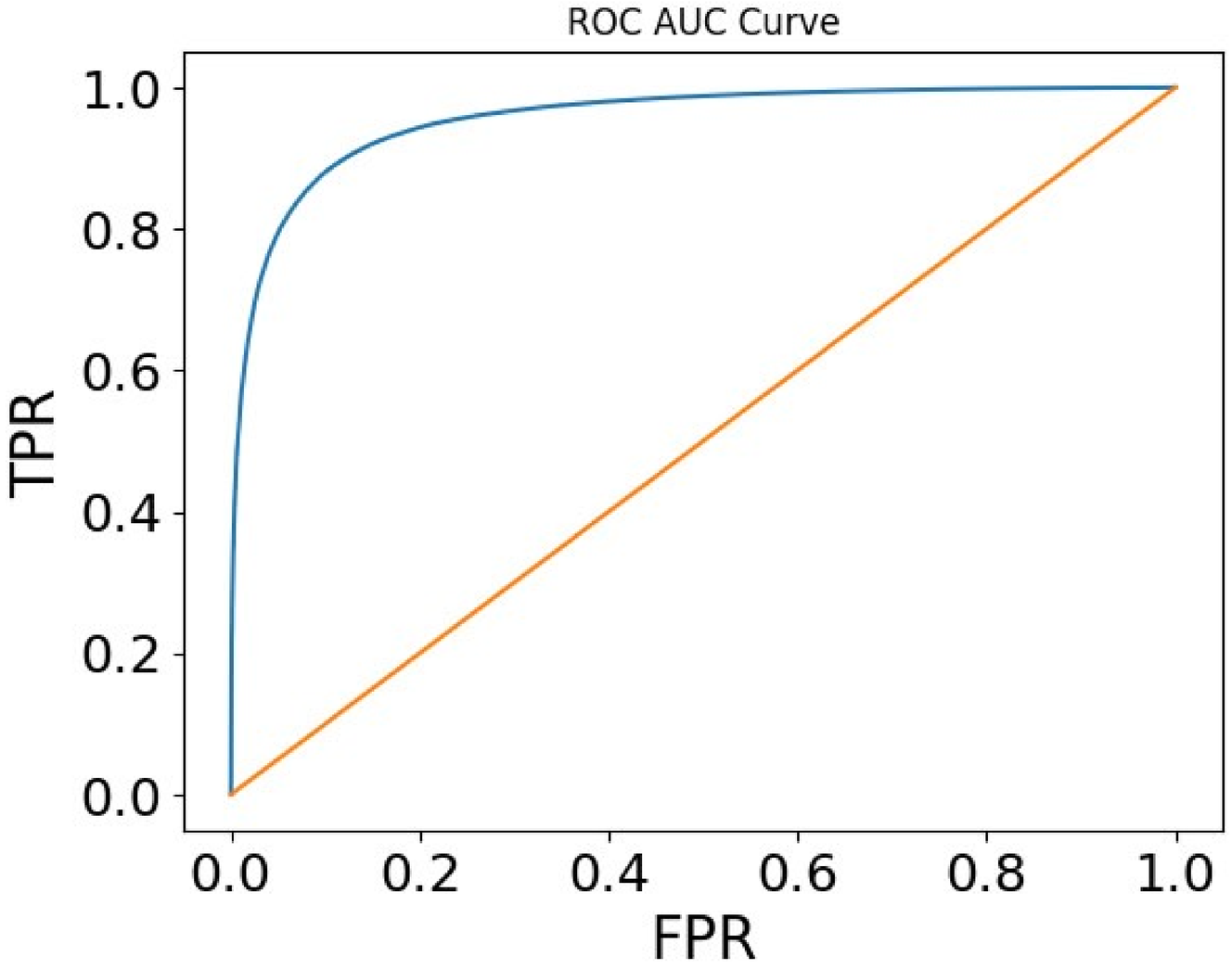
Quality metrics







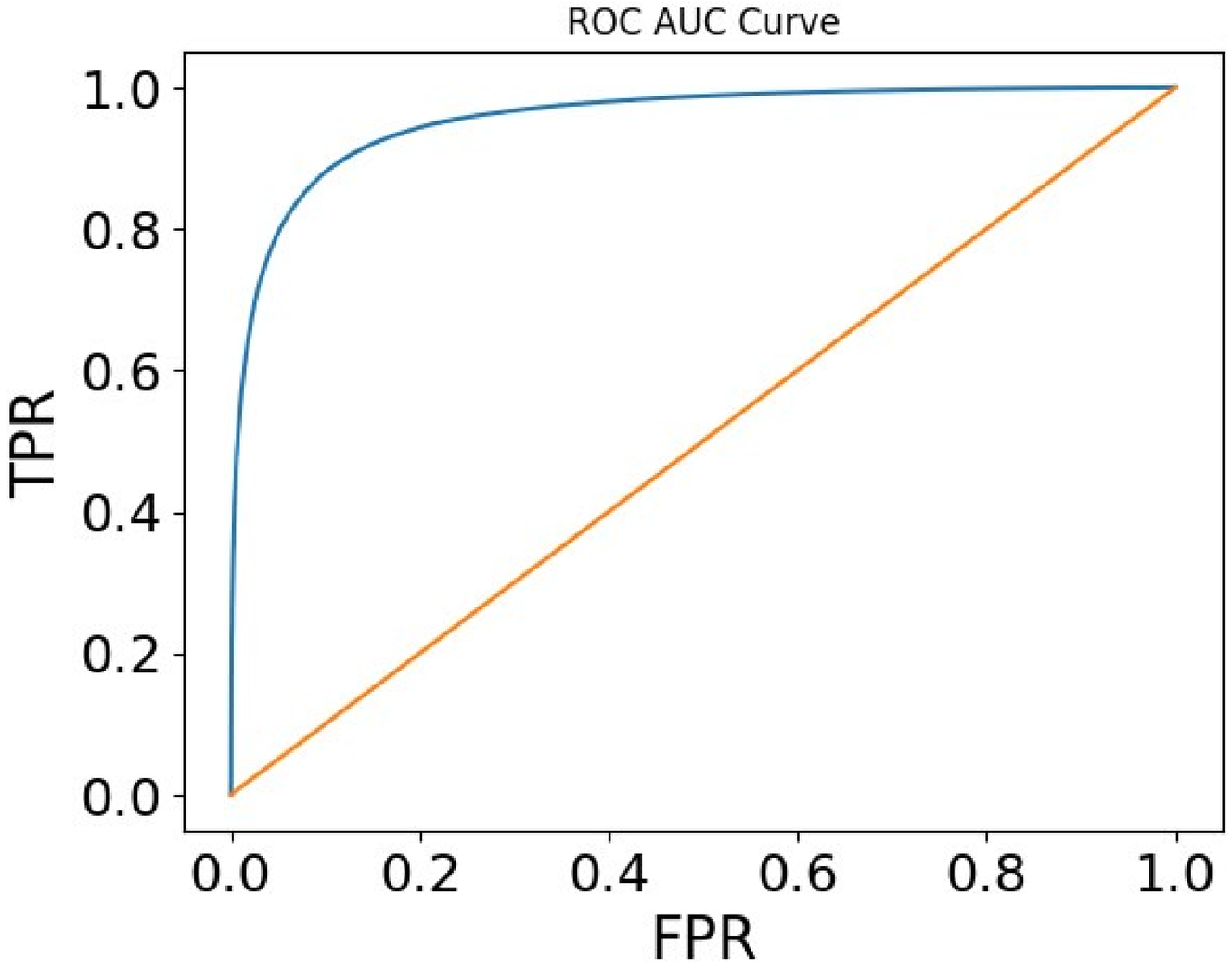
Quality metrics




```
parameters = {
    "loss":["log_loss"],
    "learning_rate": [0.01, 0.2],
    "min_samples_split": [0.01, 0.2],
    "max_depth":[8,12,16],
    "max_features":["log2","sqrt"],
    "criterion": ['squared_error'],
    "n_estimators":[10,20]
    }

clf = GridSearchCV(classif, parameters, cv=3, n_jobs=8)
```

Quality metrics

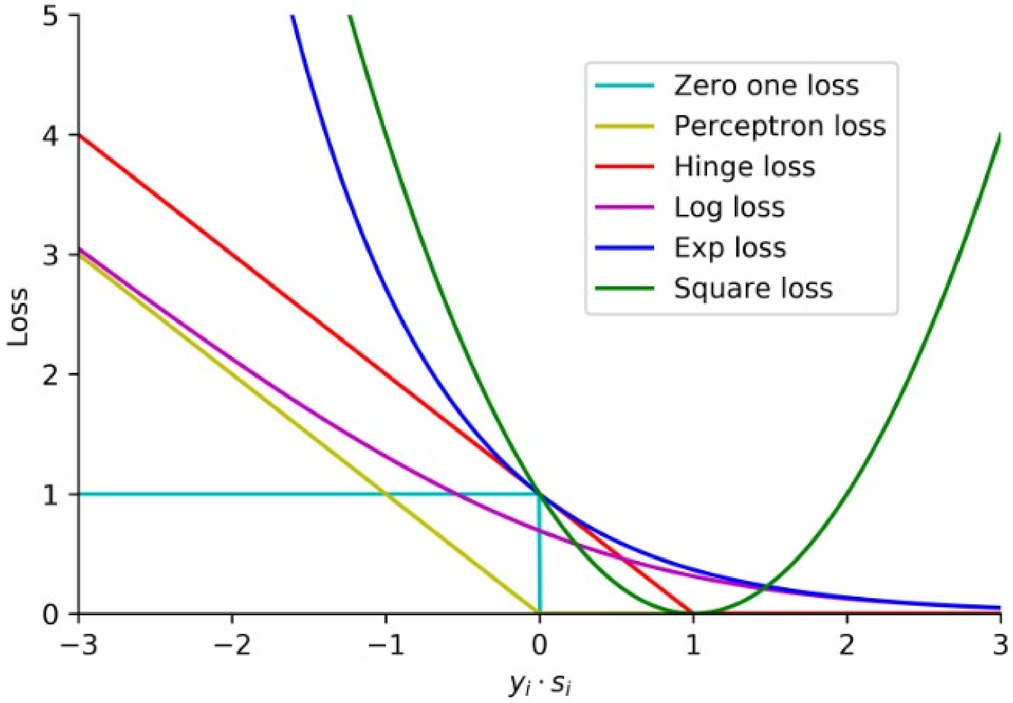


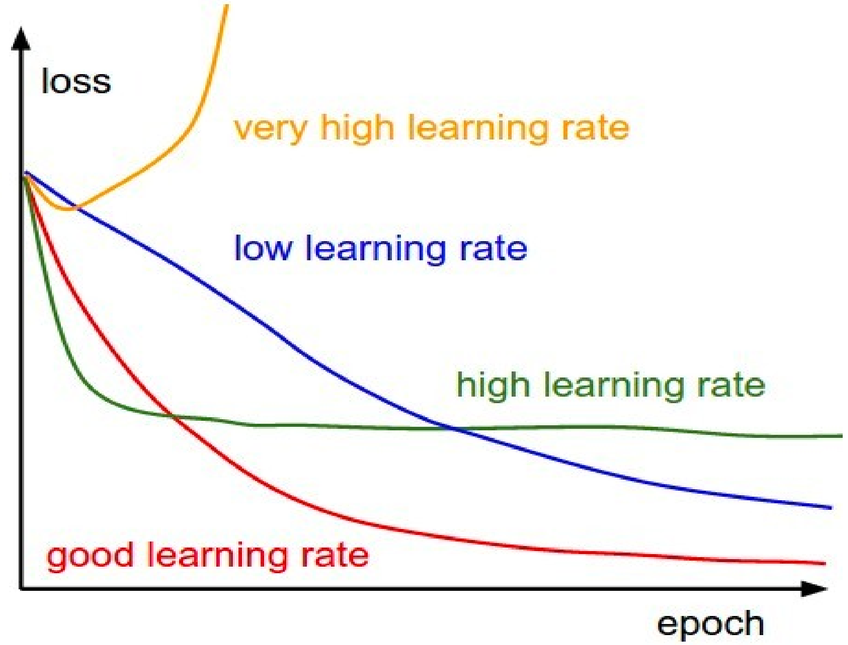
Choose wisely

1. Specific to the analysis
2. Less pars - better
3. Don’t let machine choose for you
4. Multiple treshlods – systmetic uncertainties

Regression

Regression





Choose params smartly $\omega_1, \omega_2, .., \omega_n \rightarrow \omega_1^{-1}, \omega_2^2, .., \omega_n$

Choose loss func and solver

Regression

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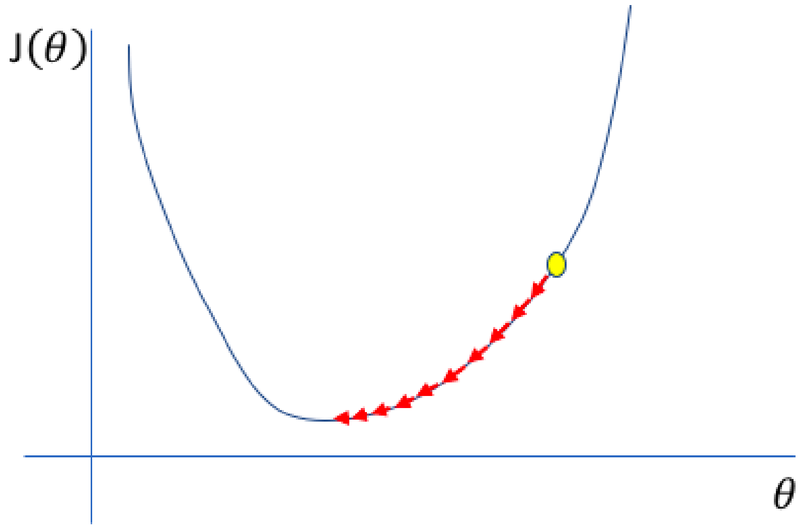
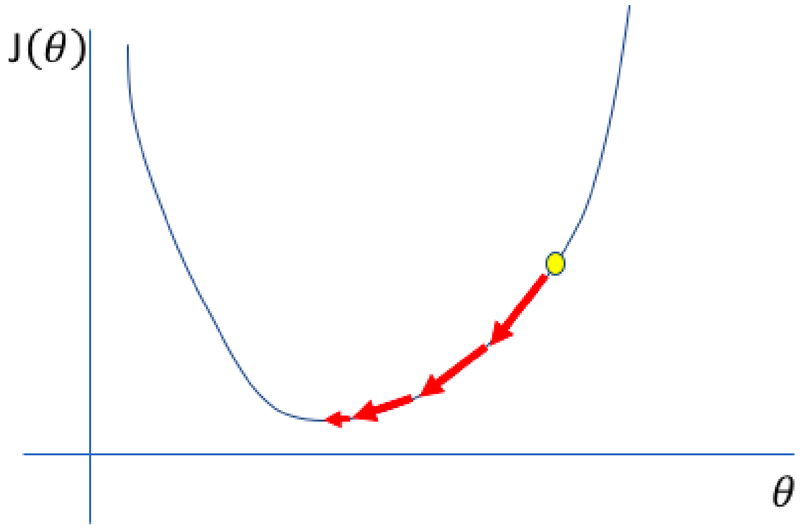
Too low



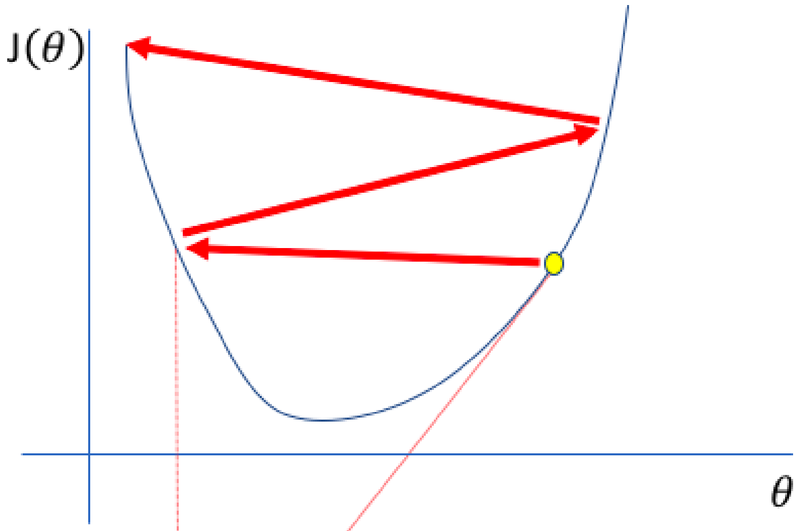
A small learning rate requires many updates before reaching the minimum point

Just right



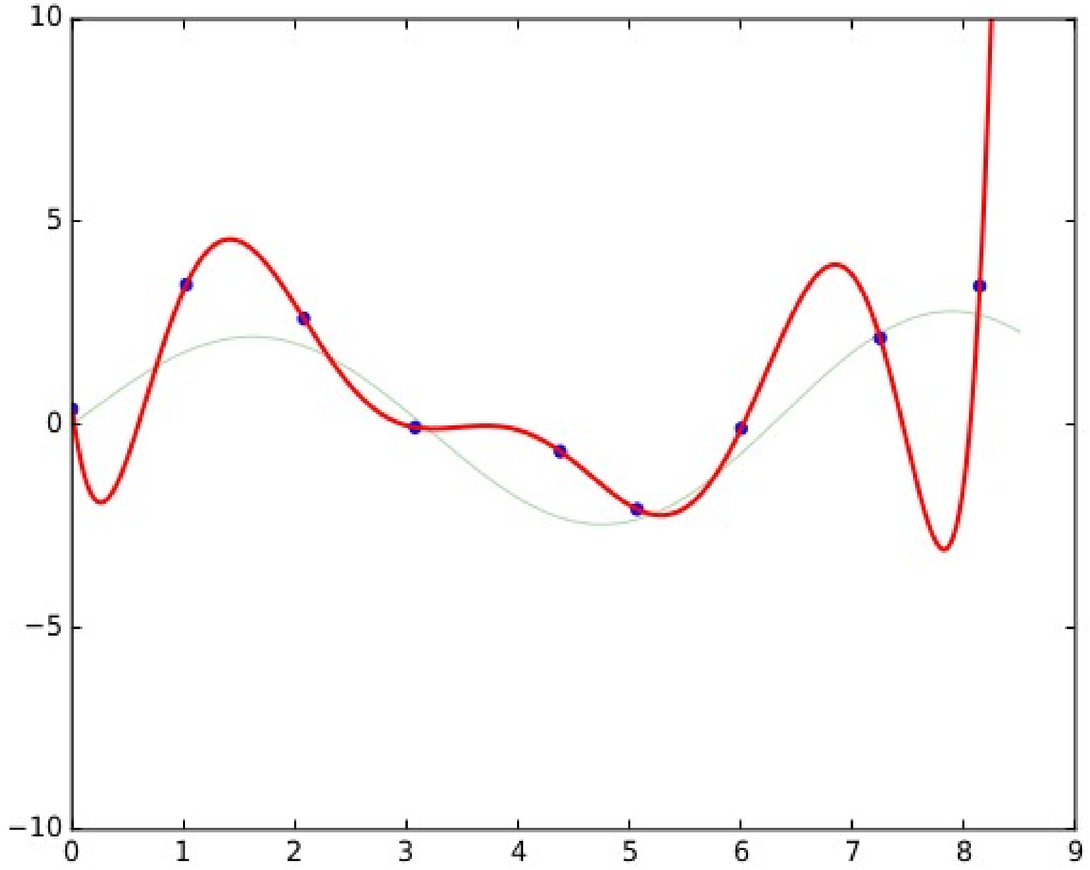
The optimal learning rate swiftly reaches the minimum point

Too high



Too large of a learning rate causes drastic updates which lead to divergent behaviors

Regression



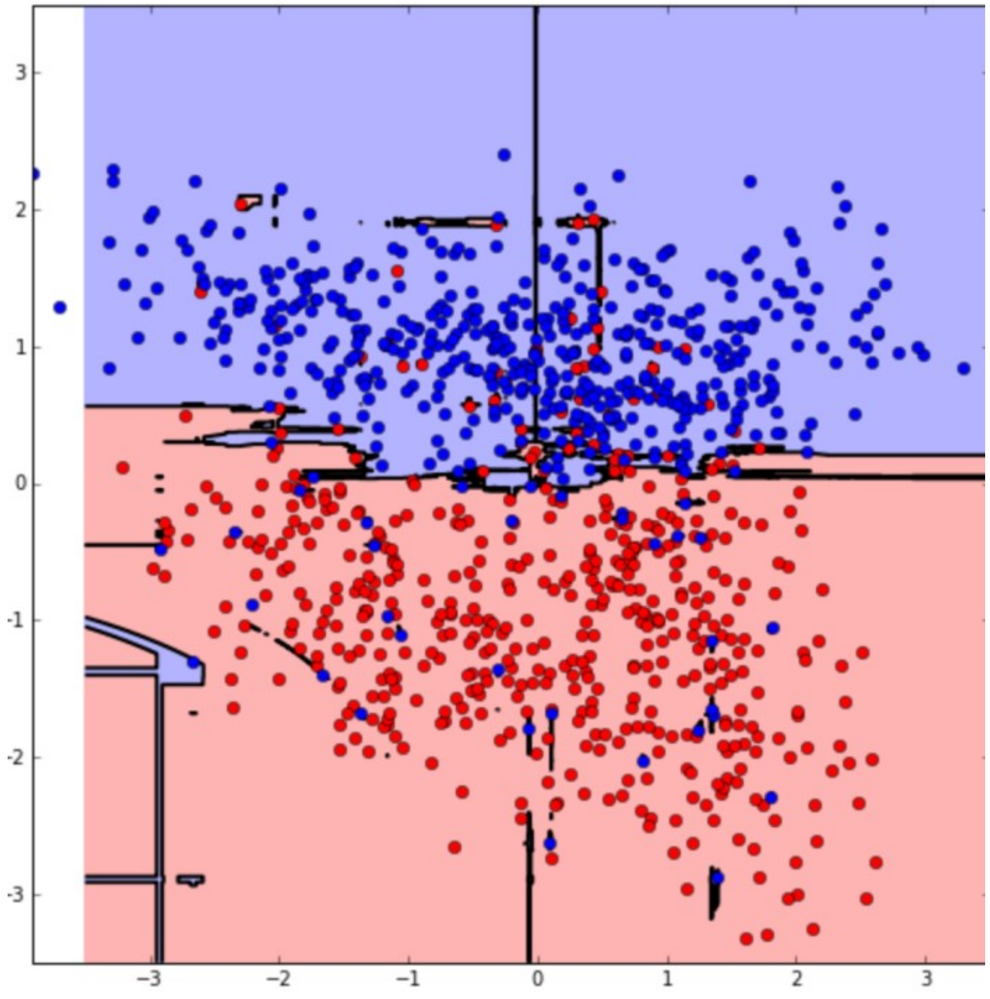
Transforming loss function by adding regularization term

$$\sum_{i=0}^{n}\left(y_i-\omega_0-\sum_{j=0}^{n}\omega_j x_{ij}\right)^2 \rightarrow$$

$$\sum_{i=0}^{m}\left(y_i-\omega_0-\sum_{j=0}^{n}\omega_j x_{ij}\right)^2+\lambda\sum_{j=0}^{m}\left|\omega_j\right|$$

Random Forest

Random Forest



Pros:

1. Robust to overfitting
2. Easy to use
3. Parallelizable
4. Classification and regression

Cons:

1. Harder to interpret
2. Slower and memory intense
3. Less accurate for small dataset

Gradient Boosting

Gradient Boosting

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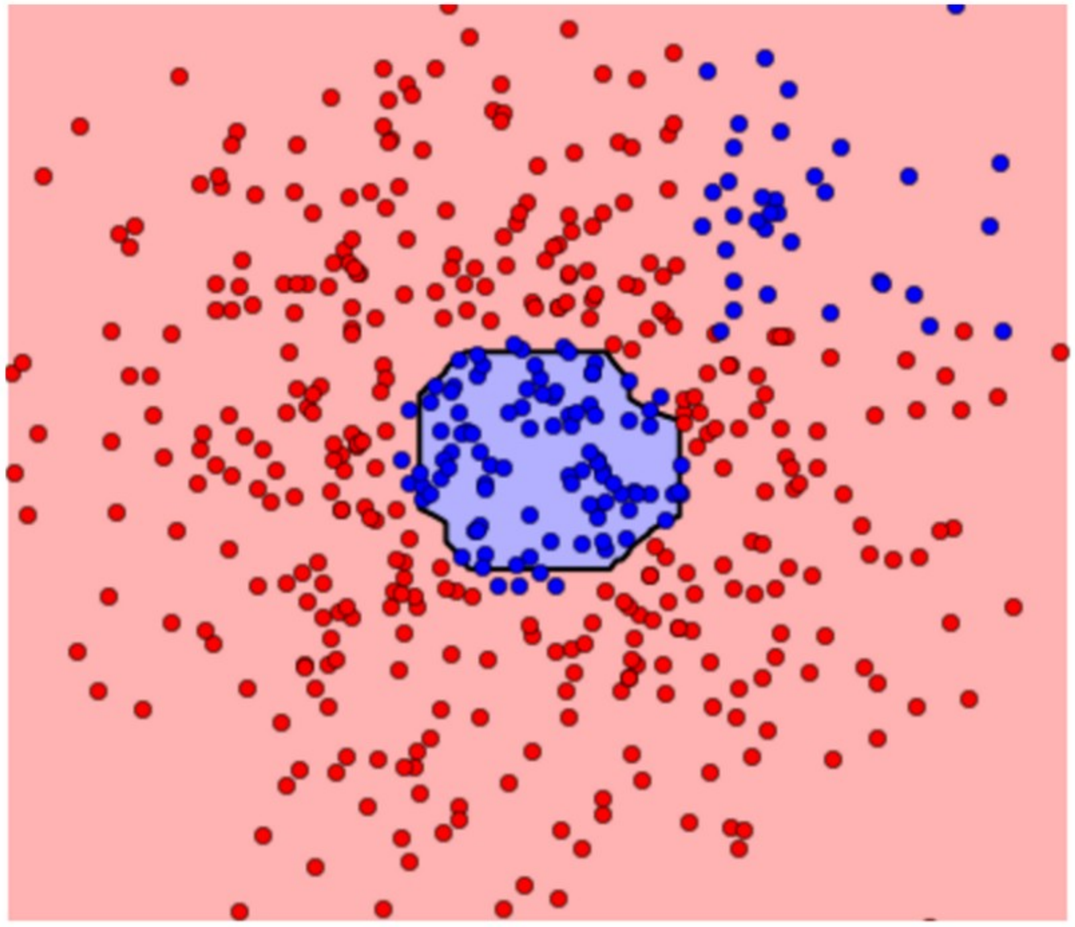
Next is fixing previous issues



Pros:

1. High accuracy
2. Handle complex tasks
3. Robust to outlier and -9999
4. Classification and regression

Cons:

1. Hard to interpret
2. Slower training
3. Sensitive to overfitting

Outline

I asked ChatGPT to summarize ML in HEP:

- Classification and Particle Identification
- Data Reconstruction
- Anomaly Detection
- Simulations and Optimization
- Data Reduction and Selection
- Hyperparameter Tuning
- Experimental Designs

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Regression

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Gradient descent