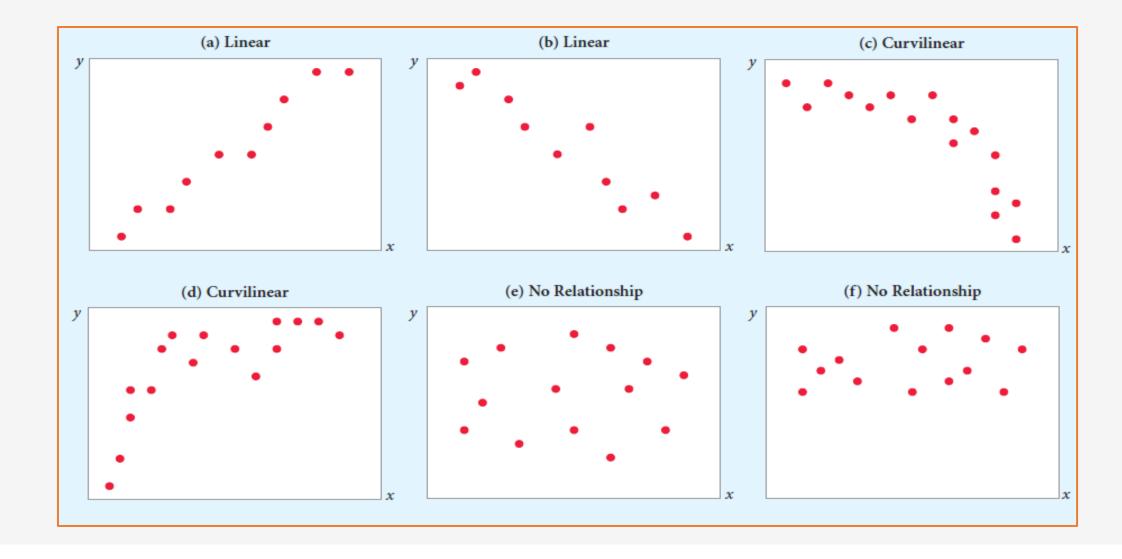
Linear Regression

Read Chapter 7 (Regression) of the Textbook

Regression Models

- To understand the application of regression analysis in data mining
 - Linear/nonlinear
 - Logistic (Logit)
- To understand the key statistical measures of fit

Relationships between variables



When the data shows linear relationship

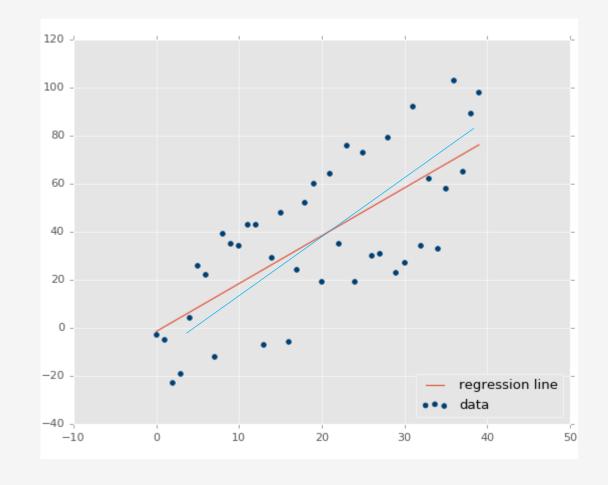
Correlation is high (positive or negative) and Scatter plots display a linear relationship

First model come to mind is

$$Y = m X + b$$

But still, there can be many lines that can "kind of" fit the data as well

Question: How to pick the "best-fit" line?



How to find the best fitting line?

Define Mean Squared Error (MSE)

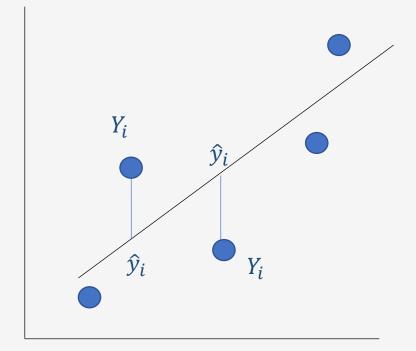
To be the square of the distance between actual and predict Y values

$$\hat{y}_i$$
 = prediction, $Y_i = actual\ value$

MSE =
$$\frac{1}{N} \sum_{i}^{n} (y_i - \hat{y}_i)^2$$

Best fitted line is the line that minimize the MSE =>

Least Square Methods



R-square as metrics for determining "goodness" of the fit

- Determining the relationship between predictor & outcome
- Relationship Among SST, SSR, SSE

$$r^{2} = SSR/SST$$

$$SST = SSR + SSE$$

$$\sum (y_{i} - \overline{y})^{2} = \sum (\hat{y}_{i} - \overline{y})^{2} + \sum (y_{i} - \hat{y}_{i})^{2}$$

where:

SST = total sum of squares SSR = sum of squares due to regression SSE = sum of squares due to error Higher R-square => Lower SSE => Better Model

R-square is 0% to 100%, anything > 70% is great

Common Theme, Toolbox and Research workflow in Data Science

Apply different algorithms to solve different problems based on the same <Theme> and <Research Workflow>

Algorithms

- SVM
- KNN
- Naïve Bayes
- Neural Network
- LogisticsRegression
- NLP



Problems

- Regression
- Classification
- RecommendationSystem
- Clustering
- Association

Common Theme, Toolbox and Research workflow in Data Science

Will use Linear Regression for many of the general practices in building models, some of them are

- Split the dataset into training set and a testing set
- Use standard metrics to judge model performance
- K-fold cross validation

Learning by doing

Linear Regression Continued

Challenges Number 1 multi-linear regressions

$$Y = beta_0 + beta_1 X_1 + beta_2 X_2 + ...$$

- Collinearity
 - Pick the factors with highest correlation first, but what about the second factors?
 - Second highest correlation coefficients or lowest correlation with the first factor, but with high enough correlation with the dependent variable
 - Solution is: find an Orthogonal independent vectors
 - PCA (Principal Components Analysis)

=> Features Engineering

Common Theme, Toolbox and Research workflow in Data Science

Apply different algorithms to solve different problems based on the same <Theme> and <Research Workflow>

Algorithms

- SVM
- KNN
- Naïve Bayes
- Neural Network
- LogisticsRegression
- NLP



Problems

- Regression
- Classification
- RecommendationSystem
- Clustering
- Association



confusion matrix bias
bias vs variance train test spilt
train test split precision vs recall
features enigneering cross validation
ularization OVERFITTING traintestsp

regularization

OVEITITING

encoding categorical var
features engineering

traintestsplit
cost function
type i error

data normalization r-square model performance type ii error

Linear Regression

Challenge Number 2:

- Relationship is NOT linear
- Solution: may become linear after transformation

```
Y = a X^2 + b X + c \implies Y = b1 Z1 + b2 Z2 + b3

where Z1 = X^2 = X

N = N_0 \exp(-lambda * t) \implies ln (N/N_0) = -lambda * t + c

=> Y = m X + b

where Y = ln (N)

X = t
```

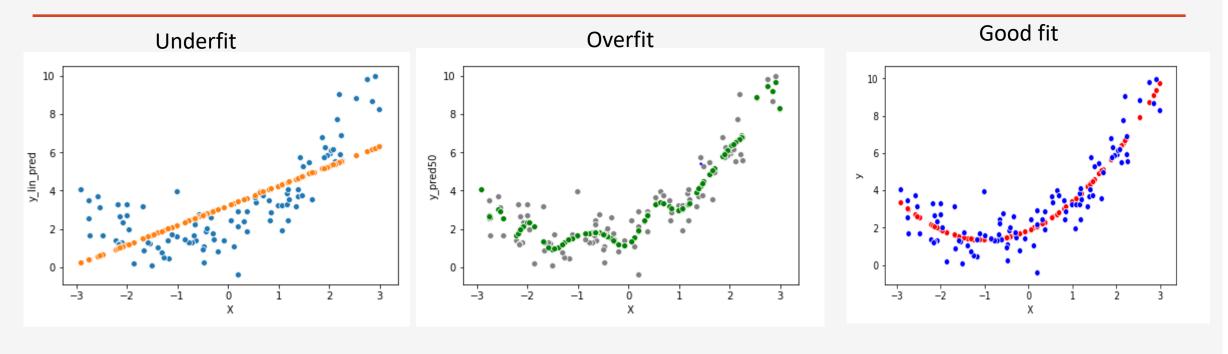
Polynomial Regression

Learning by doing

Simple vs More complicated model

- Using a model with more parameters (more features, more predictors), you are guaranteed to fit your in-sample data (training data) better
 - More parameters => R-squares always increases
- BUT it doesn't mean you have a better model
 - Adjusted R-squares (R-squares adjusted by penalizing models with more parameters)

Lesson Learned from Polynomial Regression



A more sophisticated model tends to have smaller errors in the training set, but can perform worse in testing dataset because it overfit

A too simplistic model will never be able to fit well on both the training set as well as the testing dataset

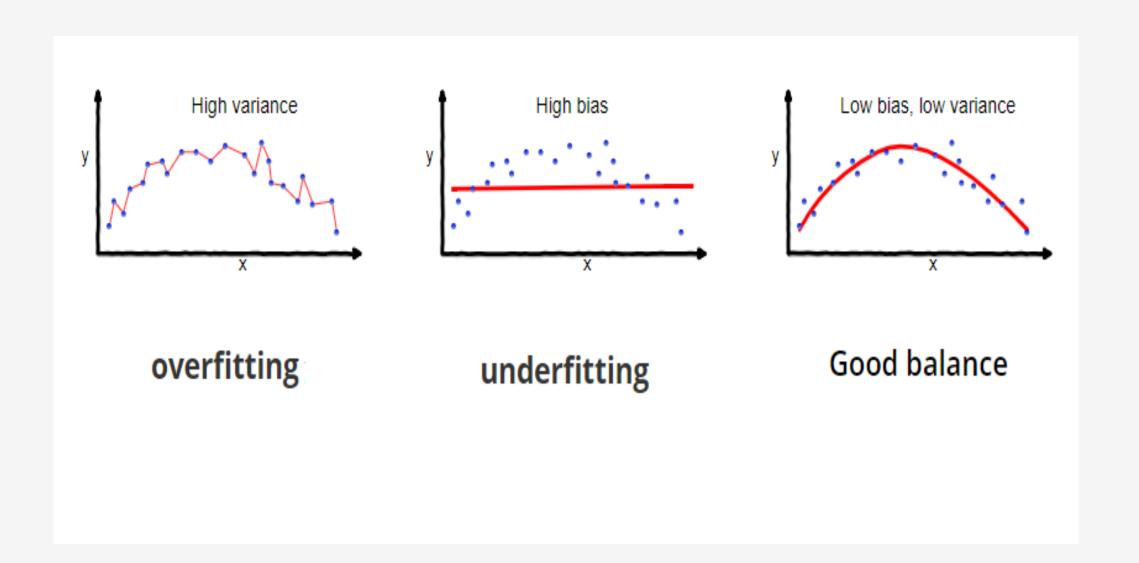
Bias vs Variance

• Bias means your model is intrinsically wrong (off, biased) that you will not fit the data well. If you use a too simplistic model, you will have high bias.

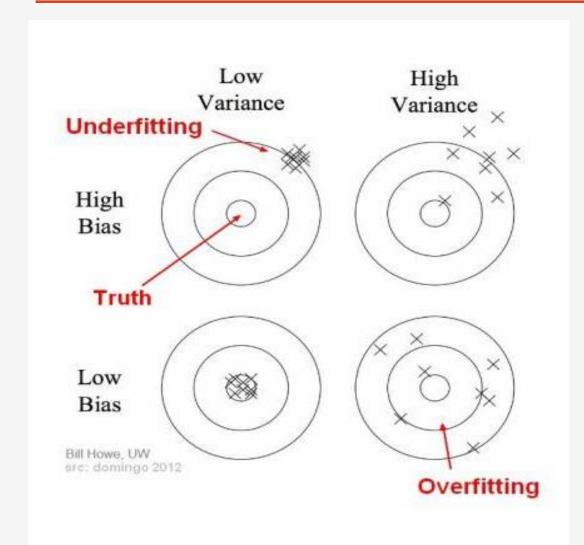
• On the other hand, using a more complicated model, you will have low bias. However, your model will not generalize well to testing dataset (out-of-sample data). The "variance" of your prediction will be high

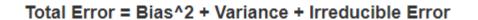
We call this the Bias vs Variance trade-off

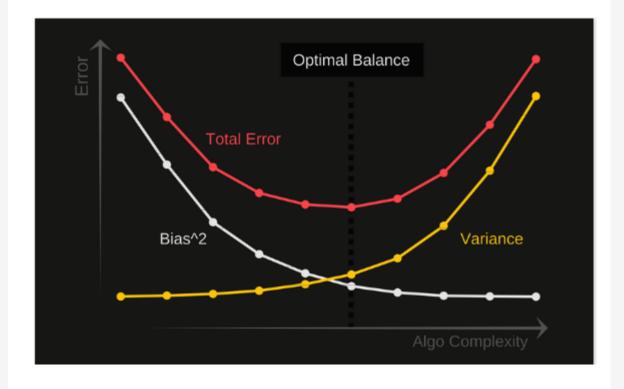
Bias vs Variance Tradeoff



Bias vs Variance Tradeoff







Recall Linear Regression can still apply to non-linear relationship

$$Y = a X^2 + b X + c \implies Y = b1 Z1 + b2 Z2 + b3$$

where $Z1 = X^2$ and $Z2 = X$

```
N = N_0 \exp(-lambda * t)
=> ln (N/N_0) = - lambda * t + c
=> Y = m X + b where Y = ln (N) and X = t
```

If $Y = log(P/(1-P)) = beta_0 + beta_1 * X_1 + beta_2 * X_2 + Beta_N + X_N$

where P is the probability of something happens

It is called Logistic Regression, which we will cover next

Classification Problem

Linear Regression: Target variable can take any numeric value

Binary Classification Problem: Target variable is either 1 or 0, Yes or No

Multi-class Classification Problem: Target variable is a list of possible values (such as classify a picture of animal as a cat, dog, bird, fish picture)

⇒ NEXT TOPICS

=>Classification Problem and Logistics Regression