

Data Mining 2

Topic 03 : Model Building

Lecture 01 : Data Modelling Overview

Dr Kieran Murphy

Department of Computing and Mathematics, WIT.
(kmurphy@wit.ie)

Spring Semester, 2021

Outline

- ML Viewpoints
- Machine learning concepts and notation
- Bias vs Variance
- Learning curves

Outline

1. Two Machine Learning Problem Perspectives	2
1.1. Three Components of a Machine Learning Problem	3
1.2. Problem–Task–Experience Perspective	7
2. Taxonomy of Machine Learning Methods	8
3. Statistical Models vs Machine Learning Models	11
4. Notation	13
4.1. DataFrame	14
4.2. Machine Learning Problems	15
5. Model Fundamentals	21
5.1. Motivation	22
5.2. The Bias–Variance Tradeoff	29
5.3. Learning Curves	32
5.4. Cross Validation Methods	34
5.5. Regularisation	38

Three Components of a Machine Learning Problem

It is easy to get lost among the multitude of choices one needs to make when given data mining problem.
A good decomposition is the following:

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
<i>K</i> -nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search
Hyperplanes	Likelihood	Branch-and-bound
Naive Bayes	Posterior probability	Continuous optimization
Logistic regression	Information gain	Unconstrained
Decision trees	K-L divergence	Gradient descent
Sets of rules	Cost/Utility	Conjugate gradient
Propositional rules	Margin	Quasi-Newton methods
Logic programs		Constrained
Neural networks		Linear programming
Graphical models		Quadratic programming
Bayesian networks		
Conditional random fields		

Three Components of a ML Problem — Representation

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
K -nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search

Representation refers to formulating the problem as a machine learning problem — typically a **classification** problem, a **regression** problem or a **clustering** problem.

- How do we represent the input?
- What **features** to use?
- How do we learn additional features?
- With each type of problem, we have multiple subtypes:
For example which classifier? a **decision tree**, a **neural network**, a **support vector machine**, etc.

Three Components of a ML Problem — Evaluation

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
K -nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search

Evaluation refers to an **objective function** or a **scoring function**, to distinguish a good model from a bad model.

- For a classification problem, we need this function to know if a given classifier is good or bad. A typical function can be based on the number of errors made by the classifier on a test set, using precision and recall.
- For a regression problem, it could be the squared error, or likelihood. Do we include regularisation? etc

Three Components of a ML Problem — Optimisation

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
K -nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search

Optimisation is concerned with searching among the models in the language for the highest scoring model.

- How do we search among all the alternatives?
- Can we use some greedy approaches, branch and bound approaches, gradient descent, linear programming or quadratic programming methods.

Data Modelling (aka Machine Learning)

As alternative to the three component (Representation / Evaluation / Optimisation) viewpoint we can think of a machine learning problem as

Definition 1 (Machine Learning)

Study of algorithms that improve their performance P at some task T with experience E .

Well defined learning task: $\langle P, T, E \rangle$

- What metric should be used to measure performance?
- What cost function should be used?
- What is the cost of incorrect prediction?
- Computational cost?

- How complex is the task?
- Task type: classification, regression, ...
- Linear vs nonlinear?
- What family of functions should be used?

- How many historical observations are needed?
- How accurate/noisy is the data?
- Do we have missing values?
- Is the data representative?

Outline

1. Two Machine Learning Problem Perspectives	2
1.1. Three Components of a Machine Learning Problem	3
1.2. Problem–Task–Experience Perspective	7
2. Taxonomy of Machine Learning Methods	8
3. Statistical Models vs Machine Learning Models	11
4. Notation	13
4.1. DataFrame	14
4.2. Machine Learning Problems	15
5. Model Fundamentals	21
5.1. Motivation	22
5.2. The Bias–Variance Tradeoff	29
5.3. Learning Curves	32
5.4. Cross Validation Methods	34
5.5. Regularisation	38

Taxonomy of Machine Learning Models ...

...by Intuition/Motivation

- **Geometric models** use intuitions from geometry such as separating (hyper-)planes, linear transformations and distance metrics.
- **Probabilistic models** view learning as a process of reducing uncertainty, modelled by means of probability distributions.
- **Logical models** are defined in terms of easily interpretable logical expressions.

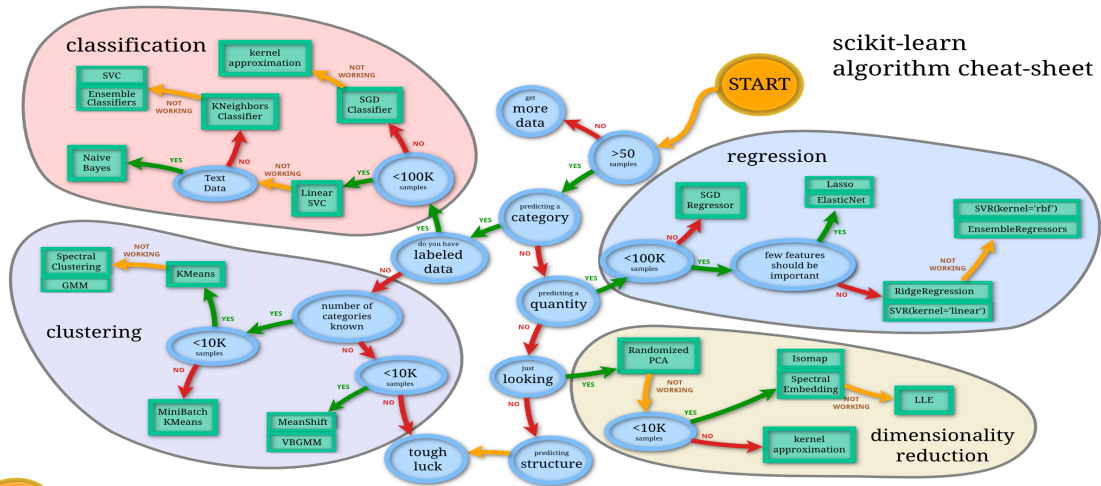
...by Algorithmic Properties

- **Regression models** predict a numeric output.
- **Classification models** predict a discrete class value.
- **Neural networks** learn based on a biological analogy.
- **Local models** predict in the local region of a query instance.
- **Tree-based models** (recursively) partition the data to make predictions.
- **Ensembles** learn multiple models and combine their predictions.

...by Fixed/Variable Number of Parameters

- **Parametric models** have a fixed number of parameters.
- In **non-parametric models** the number of parameters grows with the amount of training data.

Scikit-learn Flowchart of Models (Shallow Learners)



Outline

1. Two Machine Learning Problem Perspectives	2
1.1. Three Components of a Machine Learning Problem	3
1.2. Problem–Task–Experience Perspective	7
2. Taxonomy of Machine Learning Methods	8
3. Statistical Models vs Machine Learning Models	11
4. Notation	13
4.1. DataFrame	14
4.2. Machine Learning Problems	15
5. Model Fundamentals	21
5.1. Motivation	22
5.2. The Bias–Variance Tradeoff	29
5.3. Learning Curves	32
5.4. Cross Validation Methods	34
5.5. Regularisation	38

Statistical Models vs Machine Learning Models

Statistical Models

Data

- Usually small (< 1000 observations)
- Low dimension (< 10 variables)
- Can have detailed understanding of data
- Data is clean — human has looked at each data point

Models

- Simple models — complexity limited by theory
- Detailed/complex statistical assumptions re data
- Model known, and data is carefully examined to verify assumptions.

Validation

- Evaluation based on theoretical estimates under stated statistical assumptions
- Analysis of errors using theoretical distributions

Statistics would be very different if it had been born after the computer instead of 100 years before

ML Models

- Can be huge (million+ observations)
- Large dimension (1000+, more for vision)
- Too large for human to parse / understand
- Data not clean — humans can't afford to understand/fix each point

- “No” upper limit on model complexity
- Fewer statistical assumptions re data
- Don't know right model? No problem! have multiple models and vote/weight results

- Empirical evaluation methods instead of theory — how well does it work on **unseen** data?
- Don't calculate expected error, measure it from **unseen** data.

Splitting data into train+test(+validation) is vital

Statistical Models vs Machine Learning Models

Statistical Models

Data

- Usually small (< 1000 observations)
- Low dimension (< 10 variables)
- Can have detailed understanding of data
- Data is clean — human has looked at each data point

Models

- Simple models — complexity limited by theory
- Detailed/complex statistical assumptions re data
- Model known, and data is carefully examined to verify assumptions.

Validation

- Evaluation based on theoretical estimates under stated statistical assumptions
- Analysis of errors using theoretical distributions

Statistics would be very different if it had been born after the computer instead of 100 years before

ML Models

- Can be huge (million+ observations)
- Large dimension (1000+, more for vision)
- Too large for human to parse / understand
- Data not clean — humans can't afford to understand/fix each point

- “No” upper limit on model complexity
- Fewer statistical assumptions re data
- Don't know right model? No problem! have multiple models and vote/weight results

- Empirical evaluation methods instead of theory — how well does it work on **unseen** data?
- Don't calculate expected error, measure it from **unseen** data.

Splitting data into train+test(+validation) is vital

Statistical Models vs Machine Learning Models

Statistical Models

Data

- Usually small (< 1000 observations)
- Low dimension (< 10 variables)
- Can have detailed understanding of data
- Data is clean — human has looked at each data point

Models

- Simple models — complexity limited by theory
- Detailed/complex statistical assumptions re data
- Model known, and data is carefully examined to verify assumptions.

Validation

- Evaluation based on theoretical estimates under stated statistical assumptions
- Analysis of errors using theoretical distributions

Statistics would be very different if it had been born after the computer instead of 100 years before

ML Models

- Can be huge (million+ observations)
- Large dimension (1000+, more for vision)
- Too large for human to parse / understand
- Data not clean — humans can't afford to understand/fix each point

- “No” upper limit on model complexity
- Fewer statistical assumptions re data
- Don't know right model? No problem! have multiple models and vote/weight results

- Empirical evaluation methods instead of theory — how well does it work on **unseen** data?
- Don't calculate expected error, measure it from **unseen** data.

Splitting data into train+test(+validation) is vital

Statistical Models vs Machine Learning Models

Statistical Models

Data

- Usually small (< 1000 observations)
- Low dimension (< 10 variables)
- Can have detailed understanding of data
- Data is clean — human has looked at each data point

Models

- Simple models — complexity limited by theory
- Detailed/complex statistical assumptions re data
- Model known, and data is carefully examined to verify assumptions.

Validation

- Evaluation based on theoretical estimates under stated statistical assumptions
- Analysis of errors using theoretical distributions

Statistics would be very different if it had been born after the computer instead of 100 years before

ML Models

- Can be huge (million+ observations)
- Large dimension (1000+, more for vision)
- Too large for human to parse / understand
- Data not clean — humans can't afford to understand/fix each point
- “No” upper limit on model complexity
- Fewer statistical assumptions re data
- Don't know right model? No problem! have multiple models and vote/weight results
- Empirical evaluation methods instead of theory — how well does it work on **unseen** data?
- Don't calculate expected error, measure it from **unseen** data.

Splitting data into train+test(+validation) is vital

Statistical Models vs Machine Learning Models

Statistical Models

Data

- Usually small (< 1000 observations)
- Low dimension (< 10 variables)
- Can have detailed understanding of data
- Data is clean — human has looked at each data point

Models

- Simple models — complexity limited by theory
- Detailed/complex statistical assumptions re data
- Model known, and data is carefully examined to verify assumptions.

Validation

- Evaluation based on theoretical estimates under stated statistical assumptions
- Analysis of errors using theoretical distributions

Statistics would be very different if it had been born after the computer instead of 100 years before

ML Models

- Can be huge (million+ observations)
- Large dimension (1000+, more for vision)
- Too large for human to parse / understand
- Data not clean — humans can't afford to understand/fix each point
- “No” upper limit on model complexity
- Fewer statistical assumptions re data
- Don't know right model? No problem! have multiple models and vote/weight results
- Empirical evaluation methods instead of theory — how well does it work on **unseen** data?
- Don't calculate expected error, measure it from **unseen** data.

Splitting data into train+test(+validation) is vital

Outline

1. Two Machine Learning Problem Perspectives	2
1.1. Three Components of a Machine Learning Problem	3
1.2. Problem–Task–Experience Perspective	7
2. Taxonomy of Machine Learning Methods	8
3. Statistical Models vs Machine Learning Models	11
4. Notation	13
4.1. DataFrame	14
4.2. Machine Learning Problems	15
5. Model Fundamentals	21
5.1. Motivation	22
5.2. The Bias–Variance Tradeoff	29
5.3. Learning Curves	32
5.4. Cross Validation Methods	34
5.5. Regularisation	38

Dataset Terminology / Notation

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Survived
1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S	0
2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C	1
3	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1
4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S	1
5	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S	0
6	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	0
7	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S	0
8	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S	0
9	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S	1
10	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C	1
11	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S	1

- A labeled dataset consists of m rows $\times (n + 1)$ columns / variables.
- Use bold to represent vectors and matrices.
- Use subscripts to indicate particular **feature / attribute / column** x_j
- Use superscript in parenthesis to indicate particular **observation / instance/ case / row** $x^{(i)}$
- So $x_j^{(i)}$ (or $x_{i,j}$) is the i -th observation in the j -th feature $x_j^{(i)}$

Dataset Terminology / Notation

$n + 1$ columns / variables

X

n features / attributes / dimensions

y target

m observations / instances / cases / rows

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Survived
1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S	0
2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C	1
3	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1
4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S	1
5	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S	0
6	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	0
7	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S	0
8	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S	0
9	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S	1
10	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C	1
11	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S	1

• A labeled dataset consists of m rows \times $(n + 1)$ columns / variables.

• Use bold to represent vectors and matrices.

• Use subscripts to indicate particular feature / attribute / column x_j

• Use superscript in parenthesis to indicate particular observation / instance/ case / row $x^{(i)}$

• So $x_j^{(i)}$ (or $x_{i,j}$) is the i -th observation in the j -th feature $x_j^{(i)}$

Dataset Terminology / Notation

$n + 1$ columns / variables

X

n features / attributes / dimensions

y target

m observations / instances / cases / rows

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Survived
1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S	0
2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C	1
3	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1
4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S	1
5	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S	0
6	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	0
7	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S	0
8	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S	0
9	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S	1
10	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C	1
11	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S	1

x_j

- A labeled dataset consists of m rows \times $(n + 1)$ columns / variables.
- Use bold to represent vectors and matrices.
- Use subscripts to indicate particular **feature / attribute / column** x_j
- Use superscript in parenthesis to indicate particular **observation / instance/ case / row** $x^{(i)}$
- So $x_j^{(i)}$ (or $x_{i,j}$) is the i -th observation in the j -th feature $x_j^{(i)}$

Dataset Terminology / Notation

$n + 1$ columns / variables

X

n features / attributes / dimensions

y target

m observations / instances / cases / rows

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Survived
1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S	0
2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C	1
3	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1
4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S	1
5	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S	0
6	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	0
7	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S	0
8	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S	0
9	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S	1
10	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C	1
11	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S	1

x_j

$x^{(i)}$

- A labeled dataset consists of m rows \times $(n + 1)$ columns / variables.
- Use bold to represent vectors and matrices.
- Use subscripts to indicate particular **feature / attribute / column** x_j
- Use superscript in parenthesis to indicate particular **observation / instance/ case / row** $x^{(i)}$
- So $x_j^{(i)}$ (or $x_{i,j}$) is the i -th observation in the j -th feature $x_j^{(i)}$

Dataset Terminology / Notation

$n + 1$ columns / variables

X

n features / attributes / dimensions

y target

m observations / instances / cases / rows

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Survived
1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S	0
2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C	1
3	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1
4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S	1
5	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S	0
6	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	0
7	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S	0
8	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S	0
9	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S	1
10	2	Nasser, Mrs. Nicholas (Adele Achem)	female	14.0	1	0	237736	30.0708	NaN	C	1
11	3	Sandstrom, Miss. Marguerite Rut	female	4.0	1	1	PP 9549	16.7000	G6	S	1

x_j

$x^{(i)}$

- A labeled dataset consists of m rows \times $(n + 1)$ columns / variables.
- Use bold to represent vectors and matrices.
- Use subscripts to indicate particular **feature / attribute / column** x_j
- Use superscript in parenthesis to indicate particular **observation / instance/ case / row** $x^{(i)}$
- So $x_j^{(i)}$ (or $x_{i,j}$) is the i -th observation in the j -th feature $x_j^{(i)}$

Aside: A reminder of functions from the past ...

I

Recall the formula for the line:

$$y = \underbrace{m}_{\text{slope}} x + \underbrace{c}_{\text{intercept}}$$

where given coefficients $m \neq 0$ and c .

Examples include

$$y = 3x - 3, \quad y = -1.5x + 4, \quad y = 5x, \quad \dots$$

Now consider the collection of all possible lines — this gives us the **set/family of linear functions**, i.e., all functions of the form

$$f(x; m, c) = f(x) = mx + c$$

name input parameters formula

comma separator + semicolon between input(s) and parameter(s)

Aside: A reminder of functions from the past ...

I

Recall the formula for the line:

$$y = \underbrace{m}_{\text{slope}} x + \underbrace{c}_{\text{intercept}}$$

where given coefficients $m \neq 0$ and c .

Examples include

$$y = 3x - 3, \quad y = -1.5x + 4, \quad y = 5x,$$



Now consider the collection of all possible lines — this gives us the **set/family of linear functions**, i.e., all functions of the form

$$f(x; m, c) = f(x) = mx + c$$

name input parameters formula

comma separator + semicolon between input(s) and parameter(s)

Aside: A reminder of functions from the past ...

I

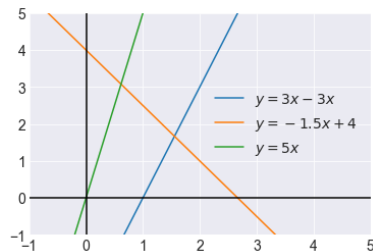
Recall the formula for the line:

$$y = \underbrace{m}_{\text{slope}} x + \underbrace{c}_{\text{intercept}}$$

where given coefficients $m \neq 0$ and c .

Examples include

$$y = 3x - 3, \quad y = -1.5x + 4, \quad y = 5x,$$



Now consider the collection of all possible lines — this gives us the **set/family of linear functions**, i.e., all functions of the form

$$f(x; m, c) = f(x) = mx + c$$

name input parameters formula

comma separator + semicolon between input(s) and parameter(s)

Aside: A reminder of functions from the past ...

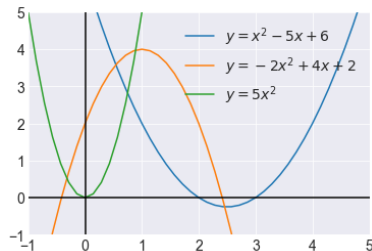
And the formula for a quadratic:

$$y = ax^2 + bx + c$$

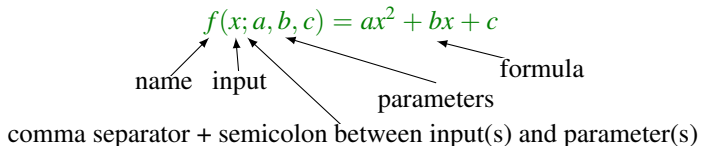
with given coefficients $a \neq 0$, b and c .

Examples include

$$y = x^2 - 5x + 6, \quad y = -2x^2 + 4x + 2, \quad y = 5x^2$$



Now consider the collection of all possible quadratics — this gives us the **family of quadratic functions**, i.e., all functions of the form



Aside: A reminder of functions from the past ...

III

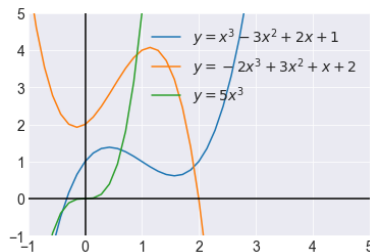
And the formula for a cubics:

$$y = a_3x^3 + a_2x^2 + a_1x + a_0$$

with given coefficients $a_3 \neq 0$, a_2 , a_1 and a_0 .

Examples include

$$y = x^3 - 3x^2 - 5x + 2x + 1, \quad y = -2x^3 + 3x^2 + x + 2, \quad y = 5x^3$$



Now consider the collection of all possible cubics — this gives us the **family of cubics functions**, i.e., all functions of the form

$$f(x; a_3, a_2, a_1, a_0) = a_3x^3 + a_2x^2 + a_1x + a_0$$

We could continue this to quartics (power of 4), quintics (power of 5), sextics (power of 6), ... or we could think about a bigger family — the family of polynomials.

Aside: A reminder of functions from the past ...

III

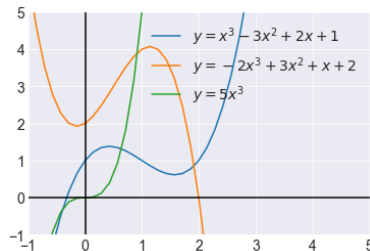
And the formula for a cubics:

$$y = a_3x^3 + a_2x^2 + a_1x + a_0$$

with given coefficients $a_3 \neq 0$, a_2 , a_1 and a_0 .

Examples include

$$y = x^3 - 3x^2 - 5x + 2x + 1, \quad y = -2x^3 + 3x^2 + x + 2, \quad y = 5x^3$$



Now consider the collection of all possible cubics — this gives us the **family of cubics functions**, i.e., all functions of the form

$$f(x; a_3, a_2, a_1, a_0) = a_3x^3 + a_2x^2 + a_1x + a_0$$

We could continue this to quartics (power of 4), quintics (power of 5), sextics (power of 6), ... or we could think about a bigger family — the family of polynomials.

Aside: A reminder of functions from the past ...

IV

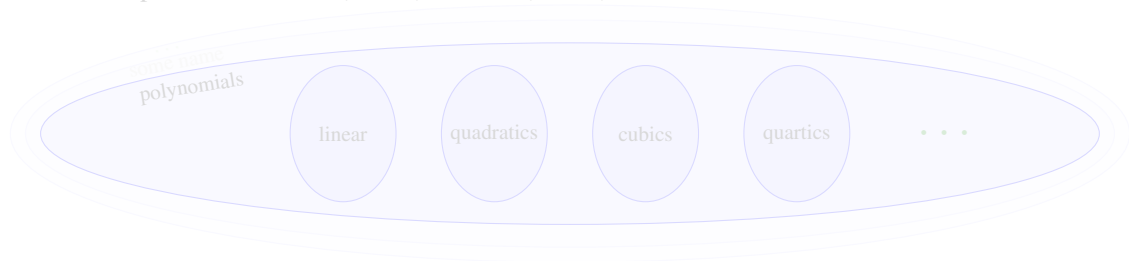
The **family of polynomials** is all functions of the form

$$f(x; \boldsymbol{\theta}) = a_n x^n + a_{n-1} x^{n-1} + \cdots a_2 x^2 + a_1 x + a_0$$

with vector $\boldsymbol{\theta} = [a_n, a_{n-1}, \dots, a_1, a_0]$.

remember we use bold font to indicate vectors.

So we end up with this idea of (nested) families (or **sets**) of functions



Note: Instead of saying “sets of sets of functions”, we often say “families of sets of functions” or “sets of families of functions”.

Aside: A reminder of functions from the past ...

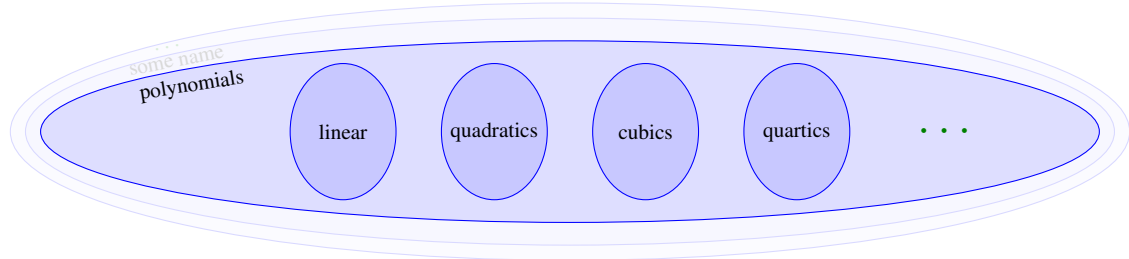
The **family of polynomials** is all functions of the form

$$f(x; \boldsymbol{\theta}) = a_n x^n + a_{n-1} x^{n-1} + \cdots a_2 x^2 + a_1 x + a_0$$

with vector $\boldsymbol{\theta} = [a_n, a_{n-1}, \dots, a_1, a_0]$.

remember we use bold font to indicate vectors.

So we end up with this idea of (nested) families (or **sets**) of functions



Note: Instead of saying “sets of sets of functions”, we often say “families of sets of functions” or “sets of families of functions”.

Aside: A reminder of functions from the past ...

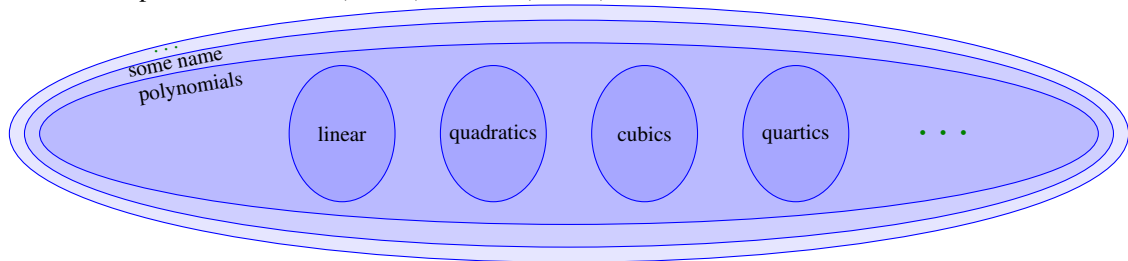
The **family of polynomials** is all functions of the form

$$f(x; \boldsymbol{\theta}) = a_n x^n + a_{n-1} x^{n-1} + \cdots a_2 x^2 + a_1 x + a_0$$

with vector $\boldsymbol{\theta} = [a_n, a_{n-1}, \dots, a_1, a_0]$.

remember we use bold font to indicate vectors.

So we end up with this idea of (nested) families (or **sets**) of functions



Note: Instead of saying “sets of sets of functions”, we often say “families of sets of functions” or “sets of families of functions”.

ML Problem Terminology

- Use hat (^) to indicate predictions.
- Use semicolon to separate arguments from parameters
- Use bold for vectors/matrices

Historical Data
 \mathbf{X}, \mathbf{y}

Cost Function
 $J(\mathbf{X}, \mathbf{y}; \boldsymbol{\theta})$

New Data
 \mathbf{X}_{new}

Modelling / Training / Fit

Sets of families of functions

\mathcal{H}

Model selection

Family of functions

$f(\mathbf{X}; \boldsymbol{\theta})$

Model optimisation, $\boldsymbol{\theta}$

$f(\mathbf{X}; \hat{\boldsymbol{\theta}}) \approx \mathbf{y}$

Prediction

$\hat{\mathbf{y}} = f(\mathbf{X}_{\text{new}}; \hat{\boldsymbol{\theta}})$

Ingredients

- Historical, labeled data
- Unseen, unlabelled data
- Sets of families of functions

Recipe

- Select a family of functions from all possible families.
- Each member of this family is uniquely determined by its parameter values. Finding the best member (function) is equivalent to finding the corresponding parameter values.
- Using a cost function (which is a measure of the difference between generated labels and given labels) we determine our optimal parameters.
- Finally using best member (function) we can generate predictions for new, unlabelled data.

ML Problem Terminology

- Use hat (^) to indicate predictions.
- Use semicolon to separate arguments from parameters
- Use bold for vectors/matrices

Historical Data
 \mathbf{X}, \mathbf{y}

Cost Function
 $J(\mathbf{X}, \mathbf{y}; \boldsymbol{\theta})$

New Data
 \mathbf{X}_{new}

Modelling / Training / Fit

Sets of families of functions

\mathcal{H}

Model selection

Family of functions

$f(\mathbf{X}; \boldsymbol{\theta})$

Model optimisation, $\boldsymbol{\theta}$

$f(\mathbf{X}; \hat{\boldsymbol{\theta}}) \approx \mathbf{y}$

Prediction

$\hat{\mathbf{y}} = f(\mathbf{X}_{\text{new}}; \hat{\boldsymbol{\theta}})$

Ingredients

- Historical, labeled data
- Unseen, unlabelled data
- Sets of families of functions

Recipe

- Select a family of functions from all possible families.
- Each member of this family is uniquely determined by its parameter values. Finding the best member (function) is equivalent to finding the corresponding parameter values.
- Using a cost function (which is a measure of the difference between generated labels and given labels) we determine our optimal parameters.
- Finally using best member (function) we can generate predictions for new, unlabelled data.

ML Problem Terminology

- Use hat ($\hat{\cdot}$) to indicate predictions.
- Use semicolon to separate arguments from parameters
- Use bold for vectors/matrices

Historical Data
 \mathbf{X}, \mathbf{y}

Cost Function
 $J(\mathbf{X}, \mathbf{y}; \boldsymbol{\theta})$

New Data
 \mathbf{X}_{new}

Modelling / Training / Fit

Sets of families of functions

\mathcal{H}

Model selection

Family of functions

$f(\mathbf{X}; \boldsymbol{\theta})$

Model optimisation, $\boldsymbol{\theta}$

$f(\mathbf{X}; \hat{\boldsymbol{\theta}}) \approx \mathbf{y}$

Prediction

$\hat{\mathbf{y}} = f(\mathbf{X}_{\text{new}}; \hat{\boldsymbol{\theta}})$

Ingredients

- Historical, labeled data
- Unseen, unlabelled data
- Sets of families of functions

Recipe

- Select a family of functions from all possible families.
- Each member of this family is uniquely determined by its parameter values. Finding the best member (function) is equivalent to finding the corresponding parameter values.
- Using a cost function (which is a measure of the difference between generated labels and given labels) we determine our optimal parameters.
- Finally using best member (function) we can generate predictions for new, unlabelled data.

Cost Functions

- Cost is a weighted sum/average over (all) cases/rows/observations.
- In each case/row/observation, i , want to measure the difference between predicted label, $\hat{y}^{(i)}$, and given label, $y^{(i)}$.
 - Simplest options are based on the difference — so we have

$$\text{cost}^{(i)} = \left| \hat{y}^{(i)} - y^{(i)} \right| \quad \text{or} \quad \text{cost}^{(i)} = \left(\hat{y}^{(i)} - y^{(i)} \right)^2$$

Absolute value $||$ or squaring is used to make sure negative and positive costs don't cancel out.

- So a possible cost function, $J(\mathbf{X}, \mathbf{y}; \boldsymbol{\theta})$ is

$$J(\mathbf{X}, \mathbf{y}; \boldsymbol{\theta}) = \frac{1}{m} \sum_{i=1}^m \left(\hat{y}^{(i)} - y^{(i)} \right)^2 \quad (\text{MSE})$$

where vector of predicted labels is $\hat{\mathbf{y}} = f(\mathbf{X}; \boldsymbol{\theta})$.

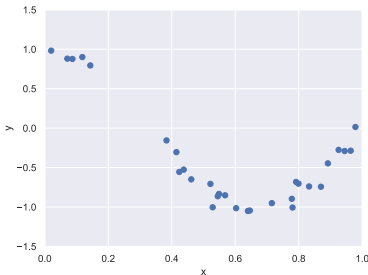
- Many, many variants:
 - Only sum over a subset of cases — stochastic gradient methods.
 - Use log functions to magnify interval between 0.1, 0.01, 0.001, etc. so we punish a model more if it is wrong with probability, say 1/1,000,000 than when it is wrong with probability 1/1,000 — cross entropy.

Outline

1. Two Machine Learning Problem Perspectives	2
1.1. Three Components of a Machine Learning Problem	3
1.2. Problem–Task–Experience Perspective	7
2. Taxonomy of Machine Learning Methods	8
3. Statistical Models vs Machine Learning Models	11
4. Notation	13
4.1. DataFrame	14
4.2. Machine Learning Problems	15
5. Model Fundamentals	21
5.1. Motivation	22
5.2. The Bias–Variance Tradeoff	29
5.3. Learning Curves	32
5.4. Cross Validation Methods	34
5.5. Regularisation	38

A Motivating Problem

Consider the problem of fitting a function to the data in following figure ...



- We will tighten the specification and work with polynomials only

$$f(x) = \theta_k x^k + \dots + \theta_2 x^2 + \theta_1 x + \theta_0$$

- Appear to have $k + 2$ parameters: the order*, k , and the $k + 1$ coefficients.
- Number of parameters is not fixed so have non-parametric method.

- However the order parameter is fundamentally different from the coefficients parameters in the impact a change in its value has (consider switching from line ($k = 1$) to quadratic ($k = 2$) to cubic ($k = 3$), etc.).
- General convention: We treat k as a **meta-parameter**[†], and treat the coefficients as **parameters**[‡], so we get a **parametric method**.

*In a polynomial the highest degree is called the **order**

[†]we decide on appropriate value ourselves

[‡]get a algorithm to determine optimum values

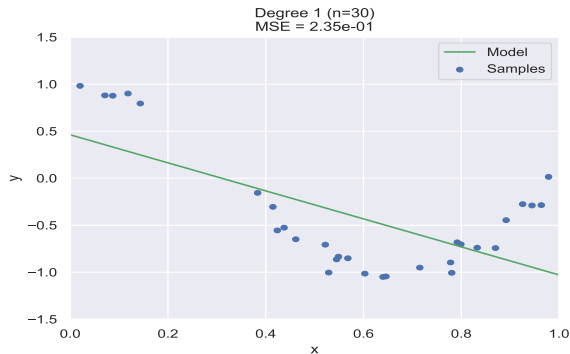
How do we pick k ?
What if we get it wrong?
How will we know?

Varying Meta-parameter, k

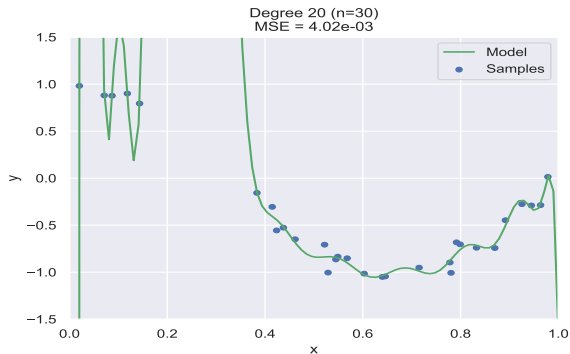
Question: What is the best fit for different values of $k = 1, 2, 3, \dots$?

Varying Meta-parameter, k

Question: What is the best fit for different values of $k = 1, 2, 3, \dots$?



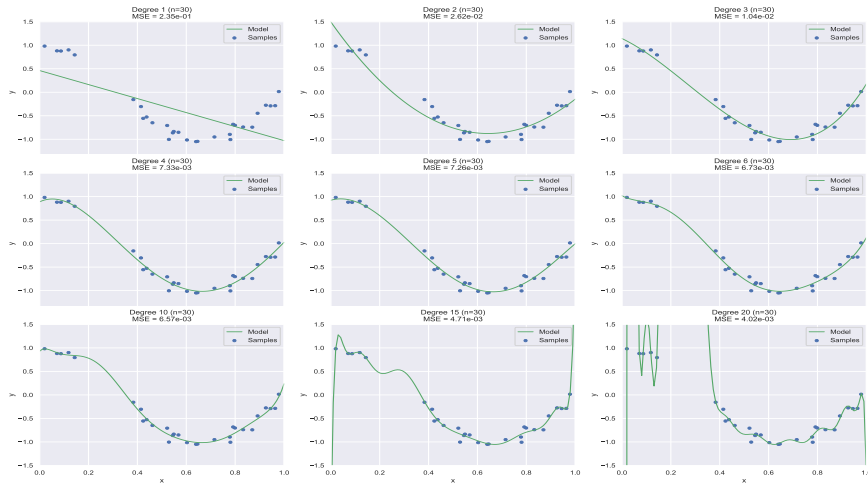
k obviously too small



k obviously too big

Varying Meta-parameter, k

Question: What is the best fit for different values of $k = 1, 2, 3, \dots$?

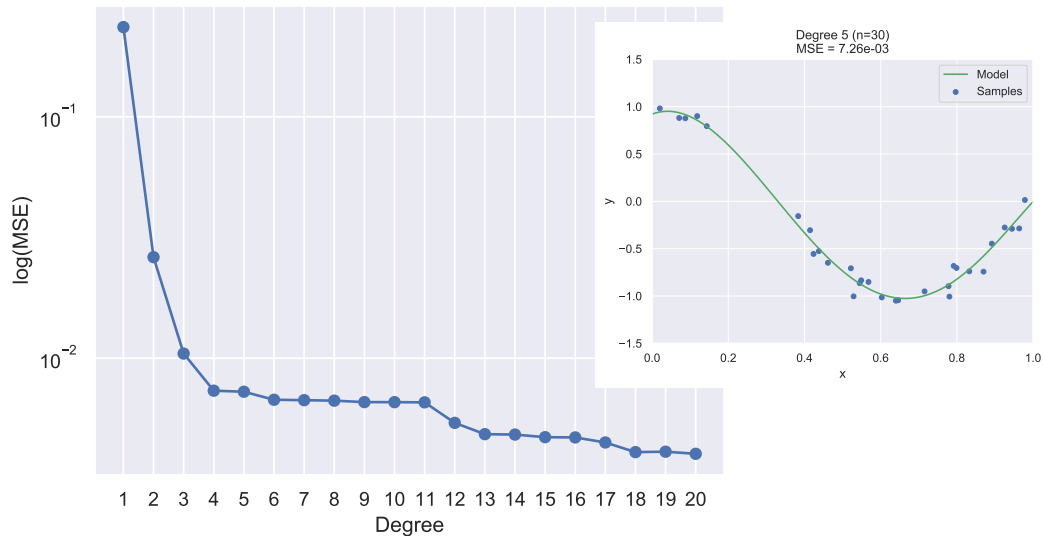


- Degree less than 3 are under-fitting, degree 10 and higher are over-fitting.
- What **objective** metric can we use to determine k ?
- Using the Mean Square Error (MSE) appears no good, it is decreasing as we increase the order.

$$MSE = \frac{1}{m} \sum (\hat{y} - y)^2$$

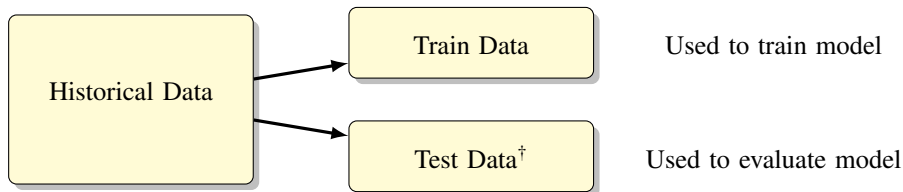
Effect of Meta-parameter on MSE

Effect of meta-parameter (k) on MSE



Splitting Historical Data in Train and Test Data

The issue is not with the MSE metric, but how we have used it.



- Using the training data for both model fitting and evaluation purposes can lead to overly optimistic estimates about the performance of the model.
- This can result in choosing a suboptimal model that performs poorly when predicting on new data.
- Now my issues are
 - *“How do we split the historical data?”*
 - *“What happens if I don’t have enough data?”*

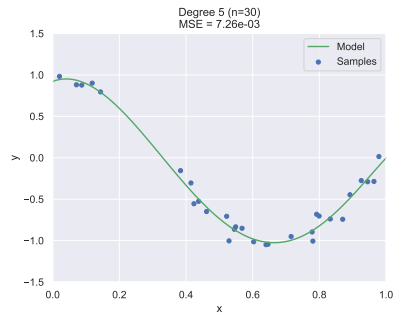
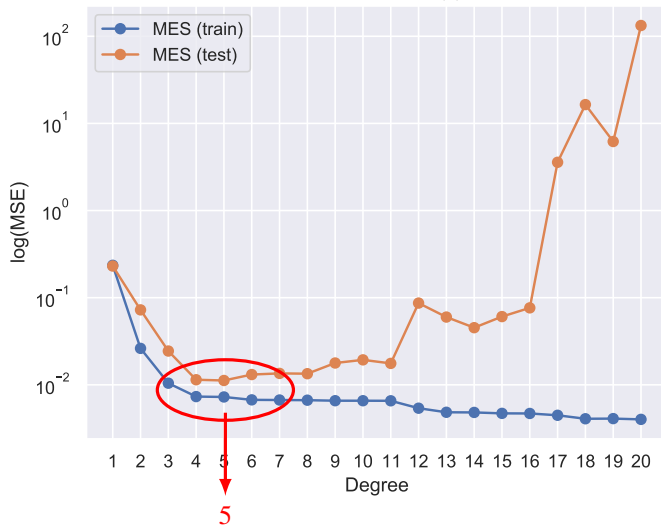
Default to train/test split of say, 60%/40%.

Use cross-validation methods.

[†]The label ‘test’ is problematic because this is often split again into ‘test’ and ‘validation’. Some practitioners, eg Andrew Ng, use the term ‘dev’ set instead.

Effect of Meta-parameter on MSE (train and test data)

Effect of meta-parameter (k) on MSE



- Method: Fit the model to the train data and then evaluate it on the previously unseen test data.
- Select value of meta-parameter based on MSE(test).

Danger of Overfitting Example: The Fukushima Power Plant Disaster

I

The problem

Want to design a power plant to withstand earthquakes. Strength of structure is measured by expected number of years between earthquakes of magnitude up to the expected failure magnitude.

Implementation

- Engineers used the **Gutenberg-Richter Law**[‡], which allows the predicting the probability of a very strong earthquake from the frequency that very weak earthquakes occur.
- This is useful because weak earthquakes[§] happen almost all the time and are recorded by geologists, so the engineers had quite a large dataset to work with.

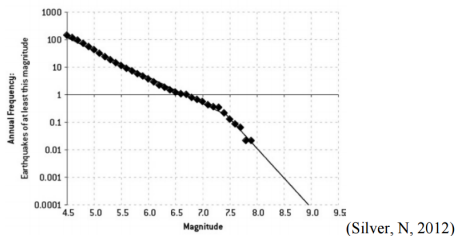
[‡]Law states that the relationship between the magnitude of an earthquake and the logarithm of the probability that it happens is linear.

[§]ones that are so weak that you can't even feel them

[¶]Source: [Machine Learning Crash Course: Part 4 - The Bias-Variance Dilemma](#)

Danger of Overfitting Example: The Fukushima Power Plant Disaster

II

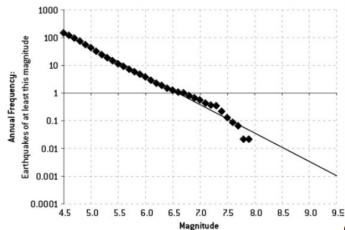
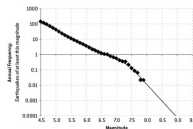


- The diamonds represent actual data while the thin line shows the model (regression). Model hugs the data points very closely. In fact, their model makes a kink at around a magnitude of 7.3.
- A linear model does not fit the data as closely (but in this case is theoretically more justified).
- When extrapolating[†] errors have an ever increasing effect.
- The 2011 earthquake that devastated the plant was of magnitude 9.

[†]Predicting outside initial data range is **extrapolating** otherwise it is **interpolating**.

Danger of Overfitting Example: The Fukushima Power Plant Disaster

II



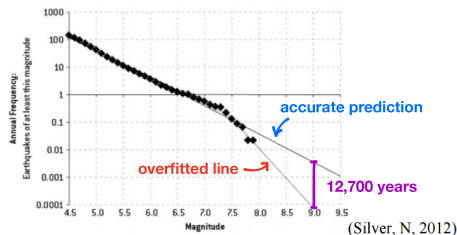
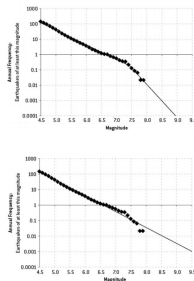
(Silver, N, 2012)

- The diamonds represent actual data while the thin line shows the model (regression). Model hugs the data points very closely. In fact, their model makes a kink at around a magnitude of 7.3.
- A linear model does not fit the data as closely (but in this case is theoretically more justified).
- When extrapolating[†] errors have an ever increasing effect.
- The 2011 earthquake that devastated the plant was of magnitude 9.

[†]Predicting outside initial data range is **extrapolating** otherwise it is **interpolating**.

Danger of Overfitting Example: The Fukushima Power Plant Disaster

II



- The diamonds represent actual data while the thin line shows the model (regression). Model hugs the data points very closely. In fact, their model makes a kink at around a magnitude of 7.3.
- A linear model does not fit the data as closely (but in this case is theoretically more justified).
- When extrapolating[†] errors have an ever increasing effect.
- The 2011 earthquake that devastated the plant was of magnitude 9.

[†]Predicting outside initial data range is **extrapolating** otherwise it is **interpolating**.

Bias and Variance

Under-fitting/over-fitting can be thought of in terms of high-bias/high-variance:

Bias

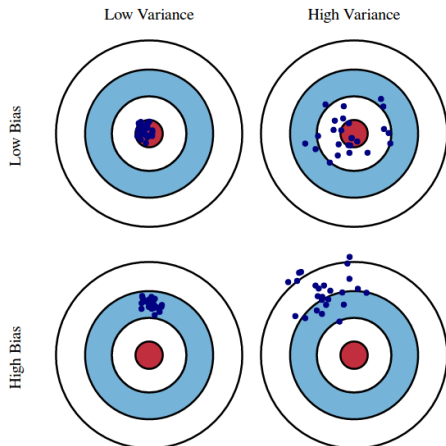
The error due to the difference between the expected (or average) prediction of our model and the correct value which we are trying to predict, over different realisations of the model.

Under-fitting results in high-bias

Variance

The error due to variance is taken as the variability of a model prediction for a given data point between different realisations of the model.

Over-fitting results in high-variance

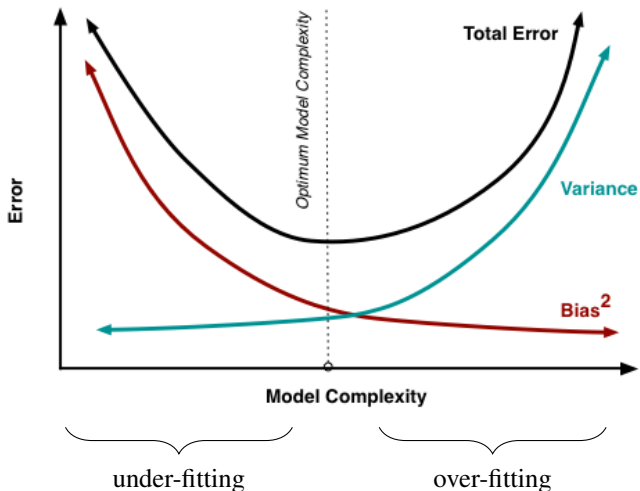


—Scott Foremann-Roe, June 2012

- The different realisations of the model can be computed by repeating the model building process over multiple datasets, or by sampling the given dataset.

Bias-Variance Tradeoff

$$\text{Error} = \text{Bias}^2 + \text{Variance} + \text{Irreducible Error}$$

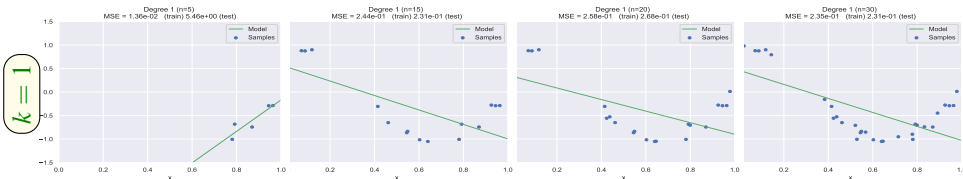


Effect of Number of Observations and Over/Under-fitting

Question: How does the best fit model change as, n , the number of observations change? ...

Effect of Number of Observations and Over/Under-fitting

Question: How does the best fit model change as, n , the number of observations change? ...



• When under-fitting (high-bias) the model is not sensitive (can't represent) to changes in the data.

• When over-fitting (high-variance) the model is too sensitive to changes in the data.

• More data helps to reduce effects of overfitting.

$n = 5$

$n = 15$

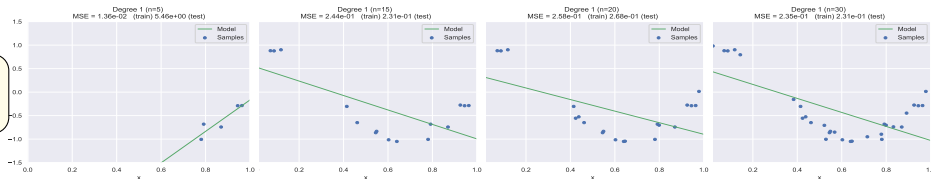
$n = 20$

$n = 30$

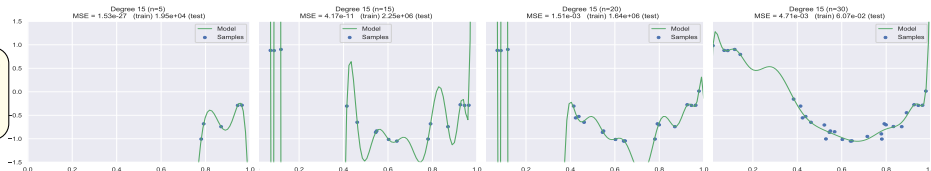
Effect of Number of Observations and Over/Under-fitting

Question: How does the best fit model change as, n , the number of observations change? ...

$k = 1$



$k = 5$



$n = 5$

$n = 15$

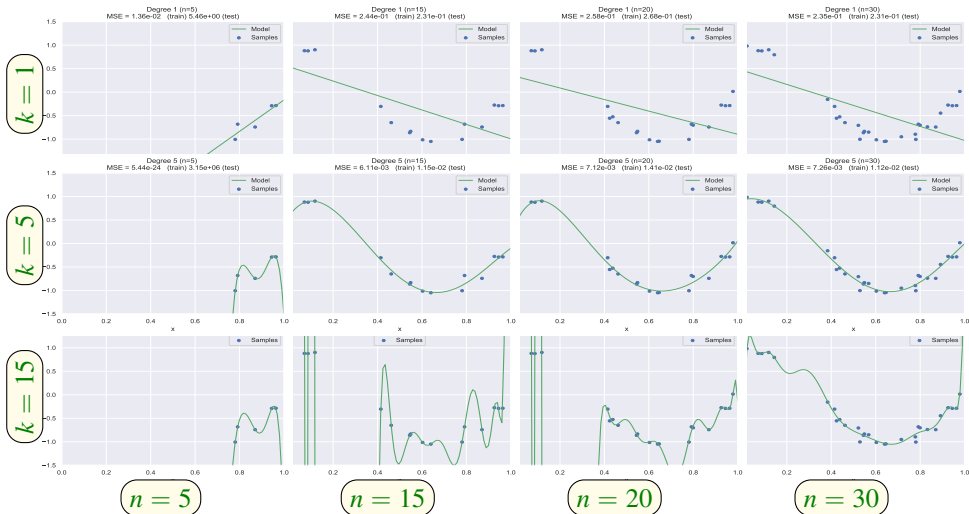
$n = 20$

$n = 30$

- When under-fitting (high-bias) the model is not sensitive (can't represent) to changes in the data.
- When over-fitting (high-variance) the model is too sensitive to changes in the data.
- More data helps to reduce effects of overfitting.

Effect of Number of Observations and Over/Under-fitting

Question: How does the best fit model change as, n , the number of observations change? ...

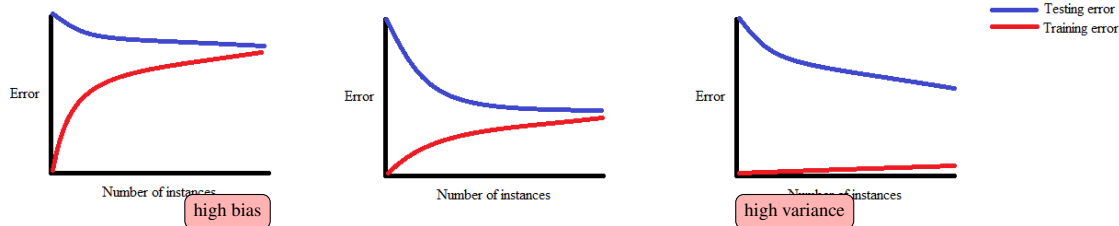


- When under-fitting (high-bias) the model is not sensitive (can't represent) to changes in the data.
- When over-fitting (high-variance) the model is too sensitive to changes in the data.
- More data helps to reduce effects of overfitting.

Learning Curves

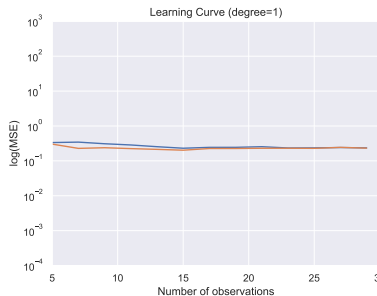
- The **learning curve** is a graph that compares the performance of a model on training and testing data over a varying number of training instances
- Should generally see performance improve as the number of training points increases.
- The comparison of performance on training and testing datasets is an indicator of how well the model can generalise to new data.
- Learning curve allows us to verify when a model has learned as much as it can about the data:
 - The performances on the training and testing sets reach a plateau.
 - There is a consistent gap between the two error rates.

Idealised Learning Curves

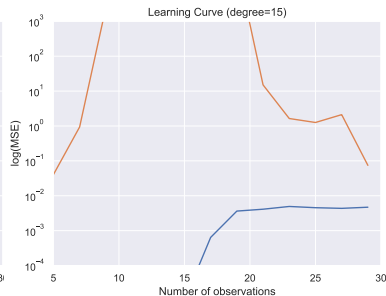
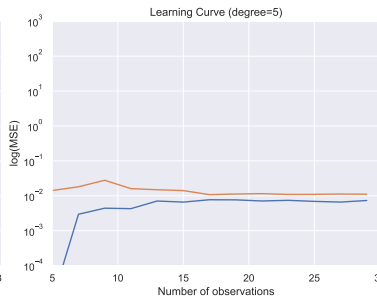


Practical Learning Curves

Real learning curves are more noisy, but the general structure is still visible — for our generated data set we have



high bias



high variance

Resolving High Bias/Variance

- High-Bias — Increase model complexity
- High-Variance — Decrease model complexity or/and increase number of observations.

Overview of Testing and Validating a Model

No single approach works, so need mixture of

- **theoretical** — various measures of statistical validity to determine whether there are problems in the data or in the model
 - Test for normality, uniform variance, ...
- **practical** — separate the data into train and test sets and evaluate on test (or validation set).
 - **accuracy** — how often/close does the model match the target?
 - Which metric should be used?
 - **reliability** — how robust is the model to different train sets?
 - How much data is needed for convergence (training)?
 - **utility** — can the model be used in practice? what is the marginal benefit of using the model?
Metrics **lift** and **gain**: the improvement that you get from using a data mining model, when you compare it to random guessing (or other model).
- **reality check** – area experts to review model.

Cross Validation Methods

Splitting the dataset into train and test data results in another source of variation, especially for small datasets. Methods that address this:

Holdout Method

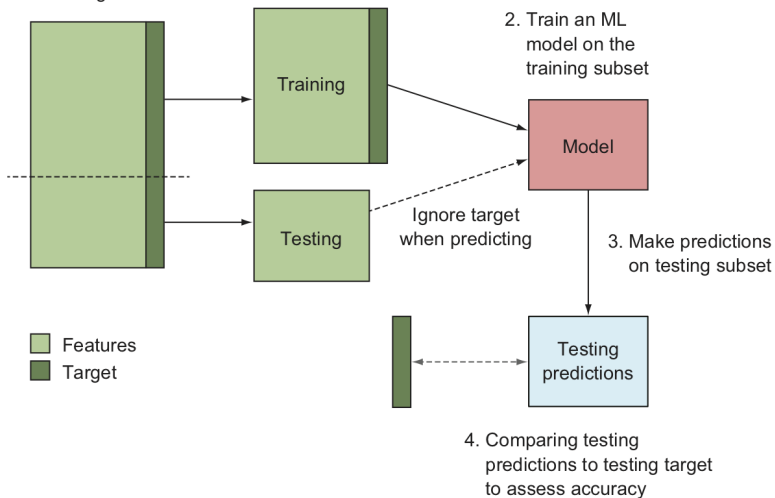
- Simplest method — just select a train/test split ratio and randomly allocate observations to train and test datasets.
- The optimal parameters from training and the error estimates on the test dataset can be noisy.

K-Fold Cross Validation

- Split the dataset into k disjoint subsets, called folds (typical choices for k are 5, 10, or 20).
- For each fold, a model is trained on all the data except the data from that fold and is subsequently used to generate predictions for the data from that fold.
- After all k -folds are cycled through, the predictions for each fold are aggregated and compared to the true target variable to assess accuracy.
- This results in noise estimate for the parameters and the error but is more computationally intensive approach than the holdout method.

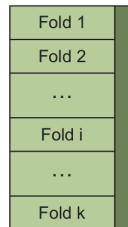
Holdout Method

1. Randomly split training instances into training and testing subsets

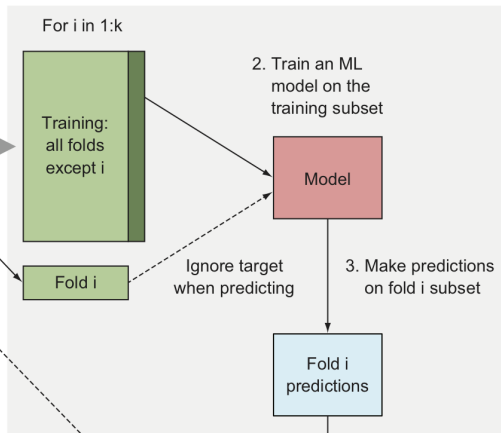


K-Fold Cross Validation

1. Randomly split training instances into k equal-sized subsets



■ Features
■ Target



2. Train an ML model on the training subset

3. Make predictions on fold i subset

5. Compare CV predictions to target to assess accuracy

4. Store fold i predictions in the CV predictions array

Regularisation

Regularisation refers to a broad range of techniques for artificially forcing models to be simpler.

- The method will depend on the type of model (learner). For example, you could prune a decision tree, use dropout on a neural network, or add a penalty parameter to the cost function in regression.
- Often times, the regularisation method is a hyper-parameter as well, which means it can be tuned through cross-validation.

Returning to our polynomial fitting problem, rather than having a cost function only based on the error (MSE) we could have

$$J = \text{MSE} + \lambda \left[(1 - \alpha) \sum_a |\theta_a|^2 + \alpha \sum_a |\theta_a| \right]$$

where

- The meta-parameter $0 < \lambda$ determines the relative importance of the regularisation term.
- The meta-parameter $0 \leq \alpha \leq 1$ determines the weighted average between the $L_2 = \sum |\theta_a|^2$ and the $L_1 = \sum |\theta_a|$ regularisation terms.