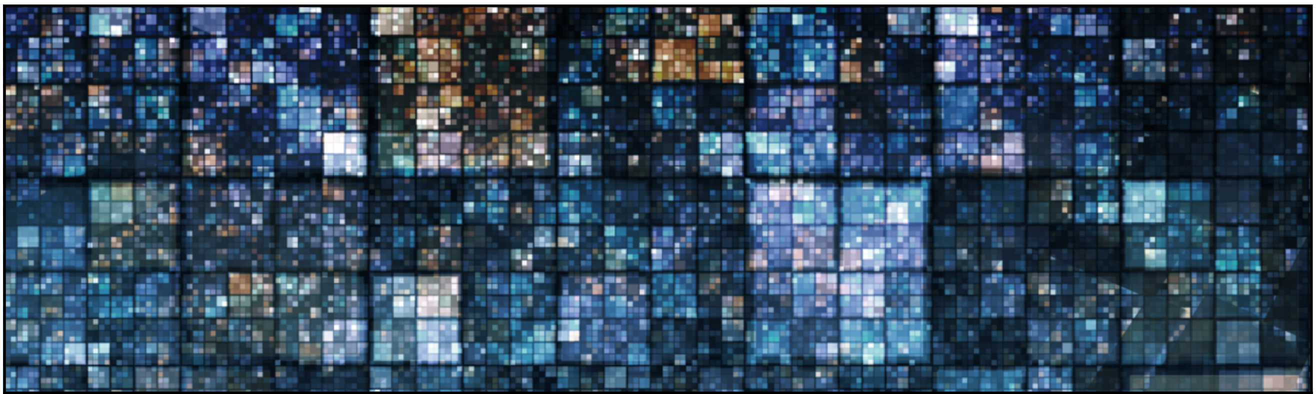

COMP47590

Advanced Machine Learning

Supervised Learning - Ensembles 1

Dr. Brian Mac Namee

Plagiarism & UCD Computer Science

- **Plagiarism is a serious academic offence**
  - [Student Code, sections 6.2 & 6.3] or [UCD Registry Plagiarism Policy] or [CS Plagiarism policy and procedures]
- Our staff and demonstrators are **proactive** in looking for possible plagiarism in all submitted work
- Suspected plagiarism is investigated by the CS Plagiarism subcommittee
  - Usually includes an interview with student(s) involved
  - 1st offence: **usually** 0 or NG in the affected components
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http://www.ucd.ie/students/guide/academicregs.html

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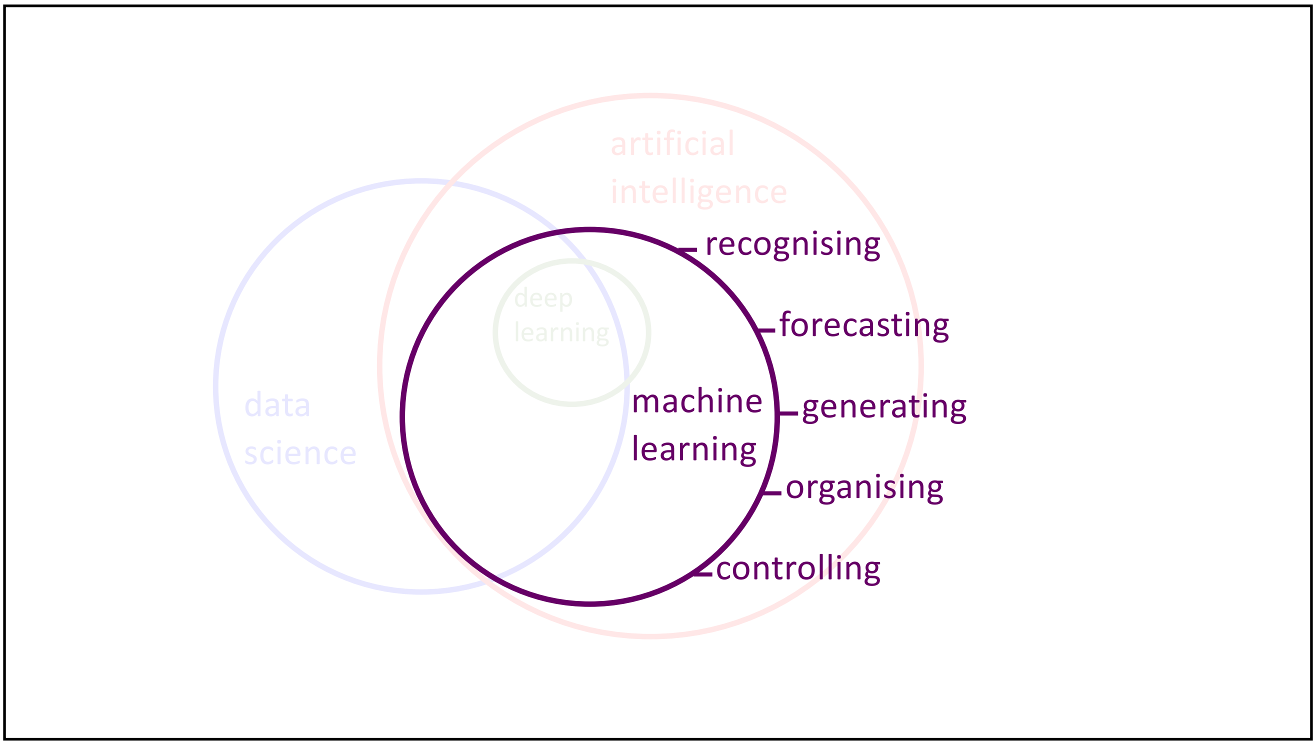
Information

Email: Brian.MacNamee@ucd.ie

Course Materials: All material posted on UCD CS moodlehttps://csmoodle.ucd.ie/moodle/course/view.php?id=663

Enrolment key **UCDAdvML2017**

SUPERVISED LEARNING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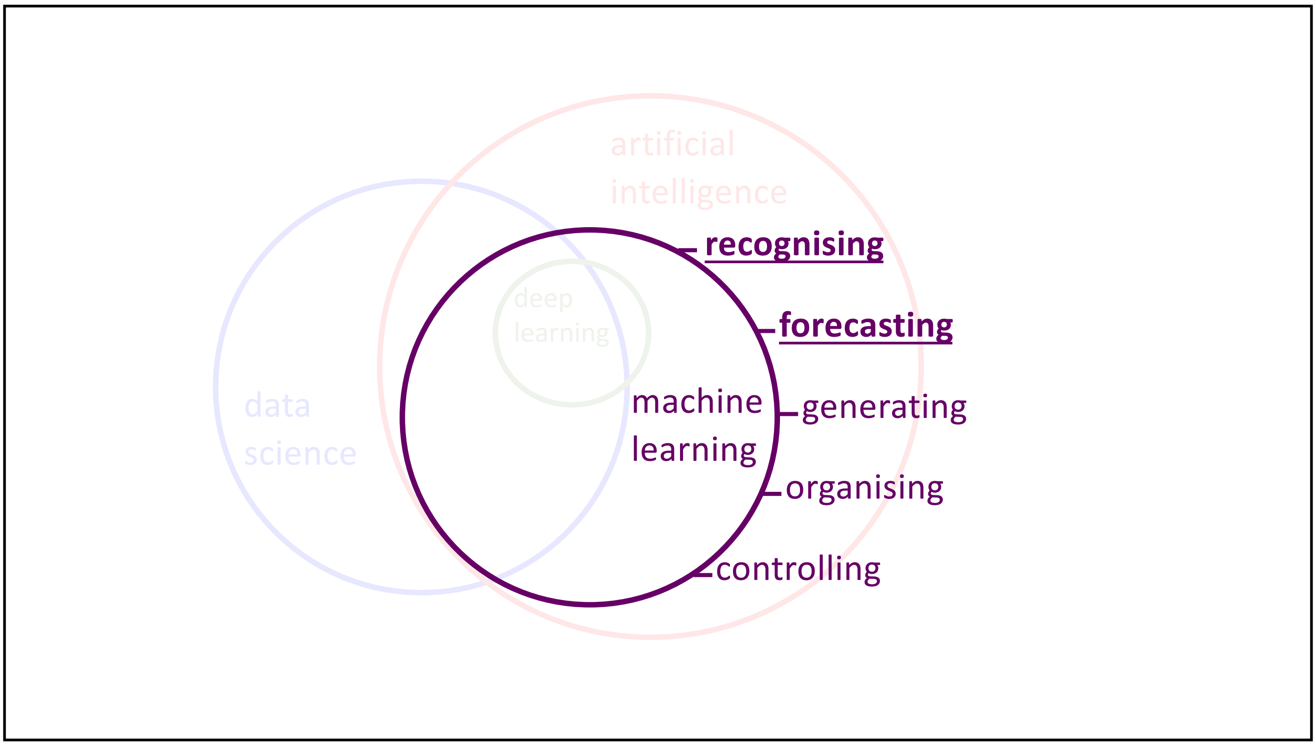
controlling


artificial
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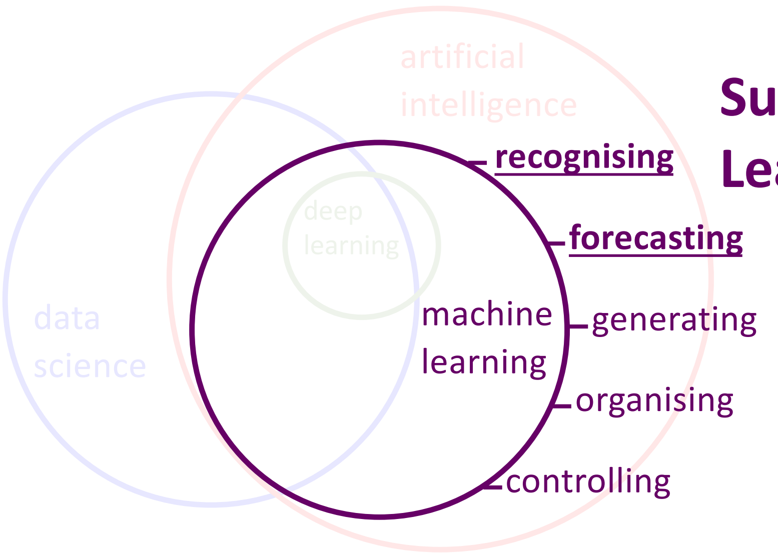
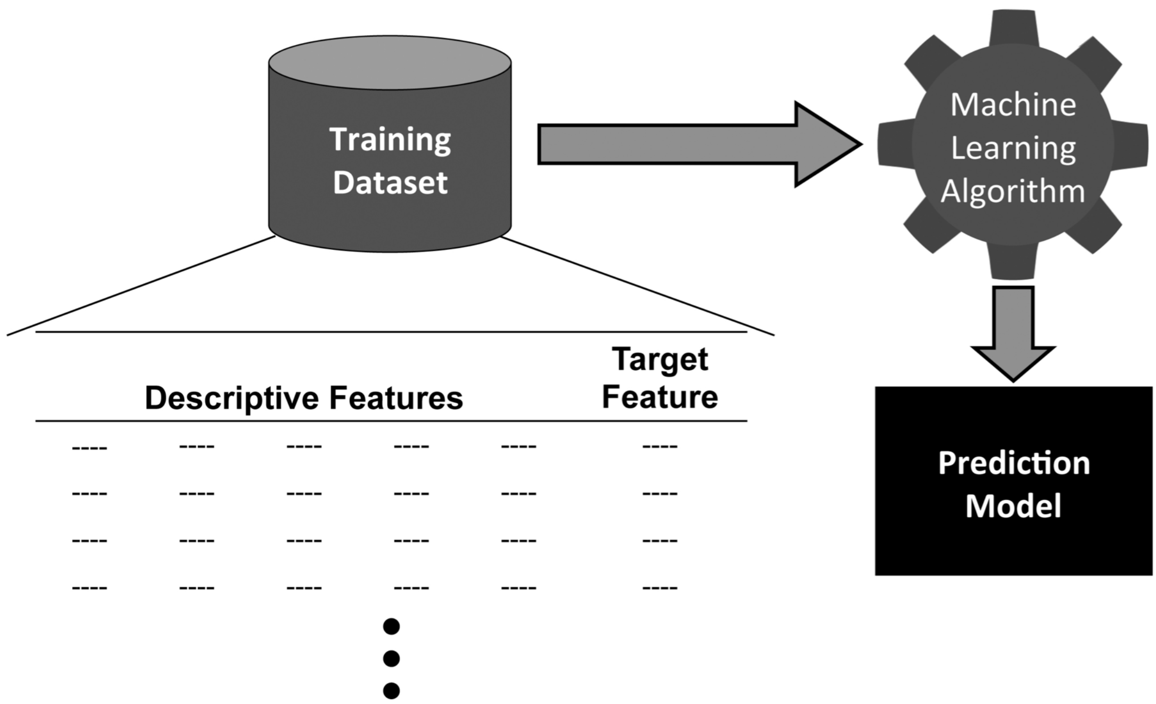
Supervised Learning





Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms, Worked Examples, and Case Studies (www.machinelearningbook.com)
John D. Kelleher, Brian Mac Namee and Aoife D'Arcy

$$\mathcal{D} = [(\mathbf{d}_1, \mathrm{t}_1), (\mathbf{d}_2, \mathrm{t}_2), \ldots, (\mathbf{d}_n, \mathrm{t}_n)]$$

where $\mathbf{d}_i$ is a set of descriptive features

$\mathbf{d}_i[0], \mathbf{d}_i[1], \ldots, \mathbf{d}_i[\mathrm{m}]$

t_i is the corresponding target feature value

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$$t = \mathbb{M}(\mathbf{q})$$

where $\mathbf{q}$ is a set of descriptive features $\mathbf{q}[0], \mathbf{q}[1], \ldots, \mathbf{q}[m]$ describing a query instance

t is a predicted target feature value

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A simple retail dataset

ID	BBY	ALC	ORG	GRP
1	no	no	no	couple
2	yes	no	yes	family
3	yes	yes	no	family
4	no	no	yes	couple
5	no	yes	yes	single

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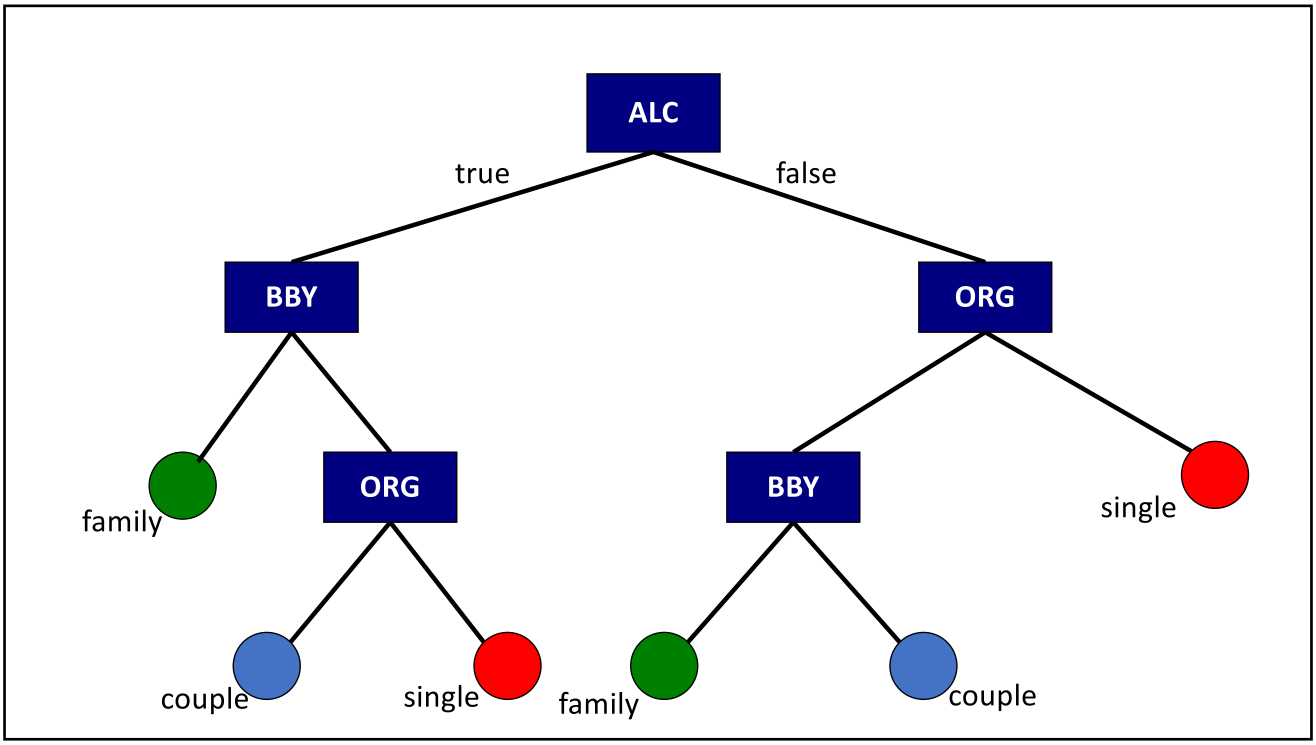
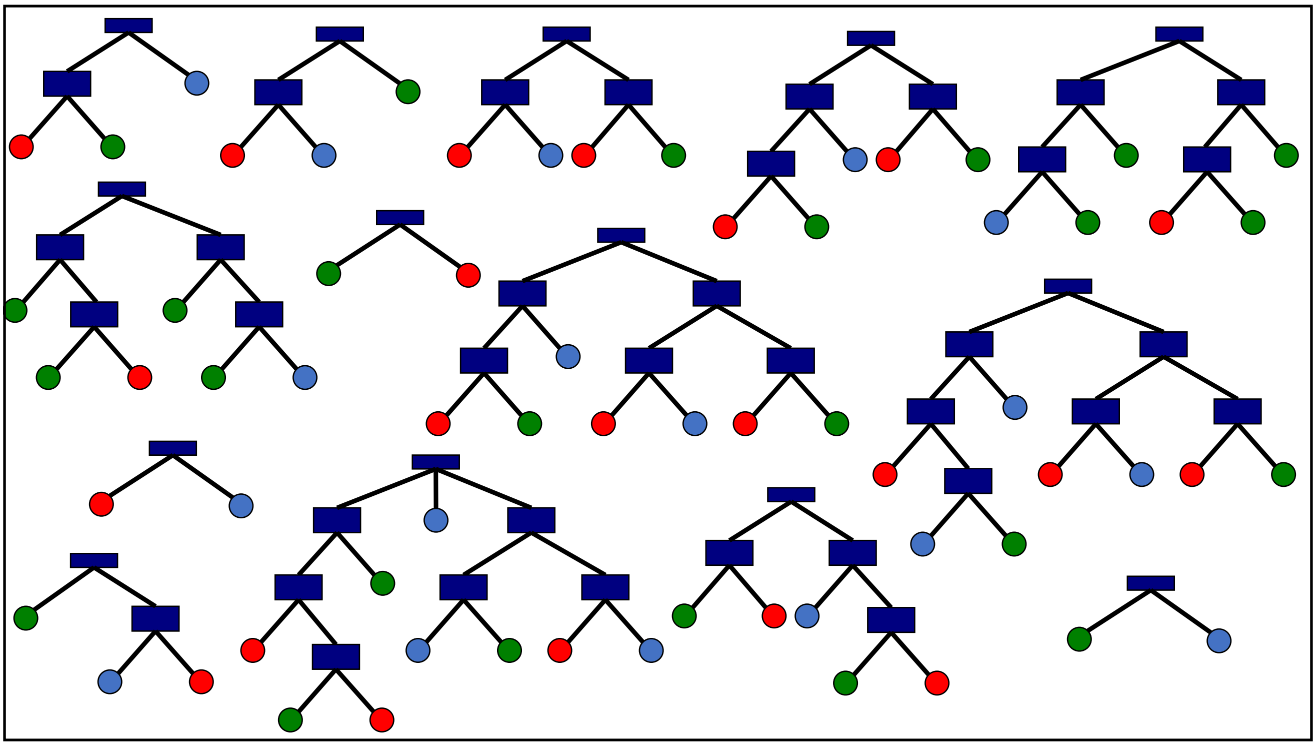
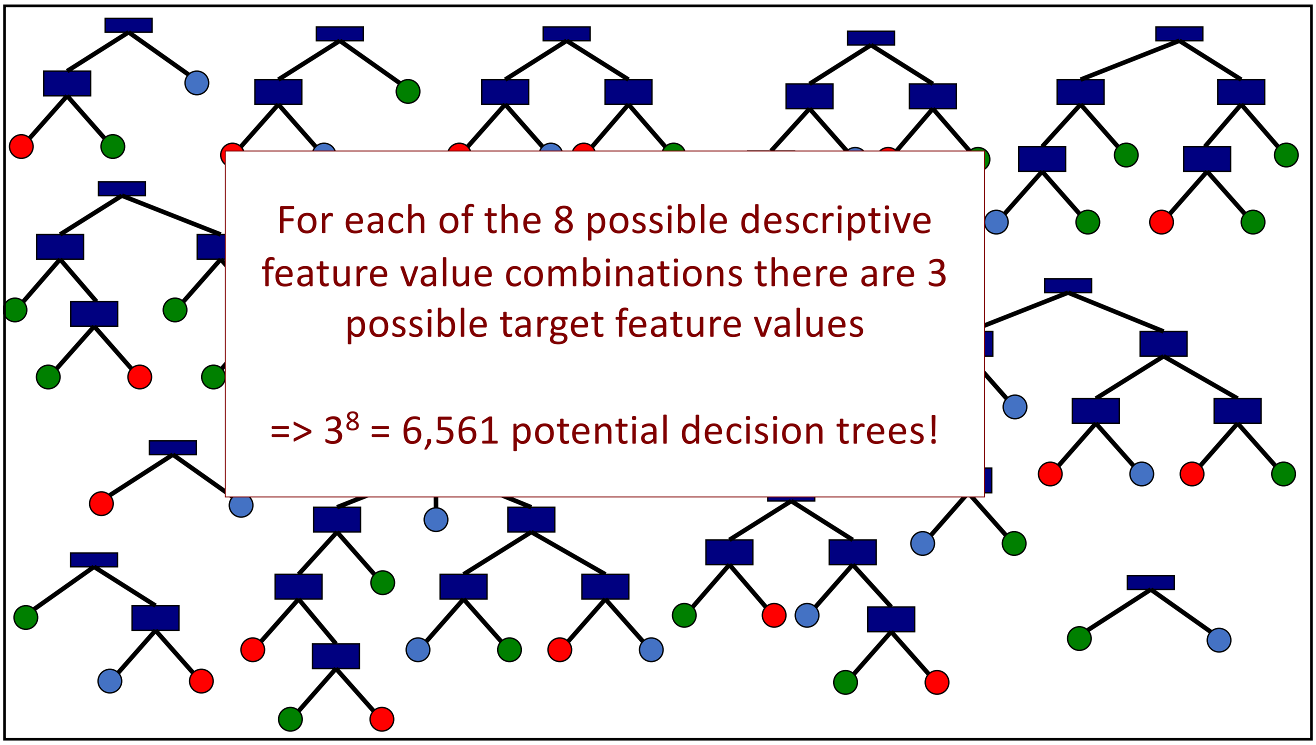

ALC
true
false
BBY
ORG
family
ORG
BBY
single
couple
single
family
couple





For each of the 8 possible descriptive feature value combinations there are 3 possible target feature values

=> 3^8 = 6,561 potential decision trees!

BBY	ALC	ORG	GRP	$\mathbb{M}_1$	$\mathbb{M}_2$	$\mathbb{M}_3$	$\mathbb{M}_4$	$\mathbb{M}_5$	...	$\mathbb{M}_{6\,561}$
no	no	no	?	couple	couple	single	couple	couple		couple
no	no	yes	?	single	couple	single	couple	couple		single
no	yes	no	?	family	family	single	single	single		family
no	yes	yes	?	single	single	single	single	single		couple
yes	no	no	?	couple	couple	family	family	family	...	family
yes	no	yes	?	couple	family	family	family	family		couple
yes	yes	no	?	single	family	family	family	family		single
yes	yes	yes	?	single	single	family	family	couple		family

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BBY	ALC	ORG	GRP	$\mathbb{M}_1$	$\mathbb{M}_2$	$\mathbb{M}_3$	$\mathbb{M}_4$	$\mathbb{M}_5$	...	$\mathbb{M}_{6\,561}$
no	no	no	couple	couple	couple	single	couple	couple		couple
no	no	yes	?	single	couple	single	couple	couple		single
no	yes	no	?	family	family	single	single	single		family
no	yes	yes	?	single	single	single	single	single		couple
yes	no	no	?	couple	couple	family	family	family	...	family
yes	no	yes	?	couple	family	family	family	family		couple
yes	yes	no	?	single	family	family	family	family		single
yes	yes	yes	?	single	single	family	family	couple		family

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no	no	no	couple	couple	couple	single	couple	couple		couple
no	no	yes	?	single	couple	single	couple	couple		single
no	yes	no	?	family	family	single	single	single		family
no	yes	yes	?	single	single	single	single	single		couple
yes	no	no	?	couple	couple	family	family	family	...	family
yes	no	yes	family	couple	family	family	family	family		couple
yes	yes	no	?	single	family	family	family	family		single
yes	yes	yes	?	single	single	family	family	couple		family

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BBY	ALC	ORG	GRP	$\mathbb{M}_1$	$\mathbb{M}_2$	$\mathbb{M}_3$	$\mathbb{M}_4$	$\mathbb{M}_5$	...	$\mathbb{M}_{6\,561}$
no	no	no	couple	couple	couple	single	couple	couple		couple
no	no	yes	couple	single	couple	single	couple	couple		single
no	yes	no	?	family	family	single	single	single		family
no	yes	yes	single	single	single	single	single	single		couple
yes	no	no	?	couple	couple	family	family	family	...	family
yes	no	yes	family	couple	family	family	family	family		couple
yes	yes	no	family	single	family	family	family	family		single
yes	yes	yes	?	single	single	family	family	couple		family

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Consistency?

Consistency ≈ memorizing the dataset

Consistency with noise in the data isn't desirable

Coverage through memorization is never possible in real problems

Consistency?

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Consistency with noise in the data isn't desirable

Coverage through memorization is never possible in real problems

GOAL: a model that **generalises** beyond the dataset and that **invariant** to the noise in the dataset

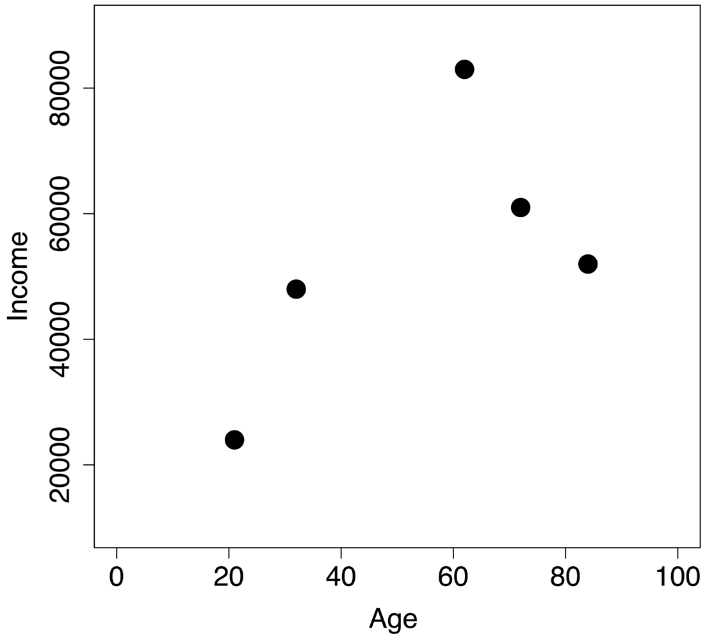
Inductive Bias

The solution is **inductive bias**, a set of assumptions that define the model selection criteria of an ML algorithm

There are two types of bias that we can use:

- restriction bias
- preference bias

Inductive bias is necessary for generalisation


Income
80000
60000
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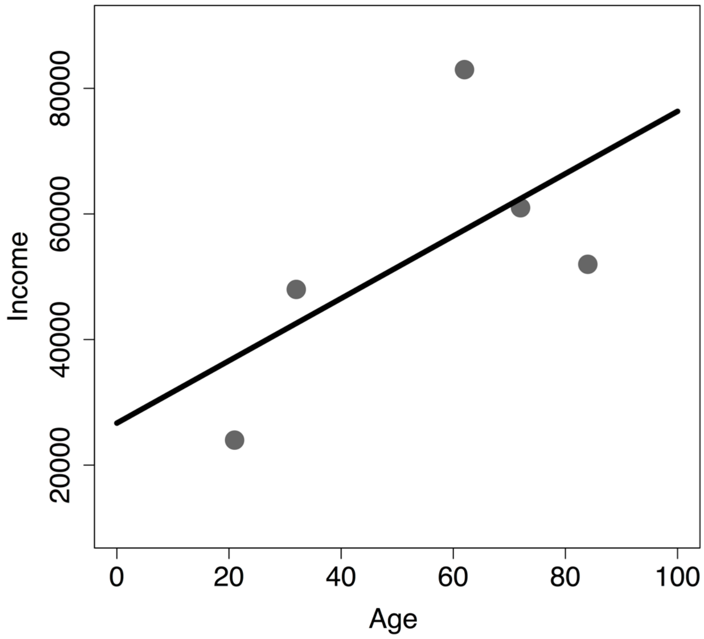
20000
0
20
40
60
80
100
Age


Income
80000
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80
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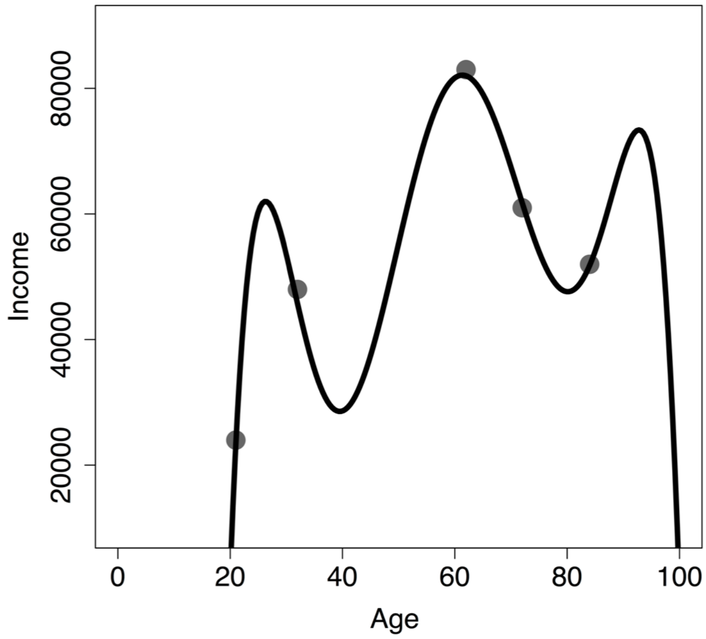
Age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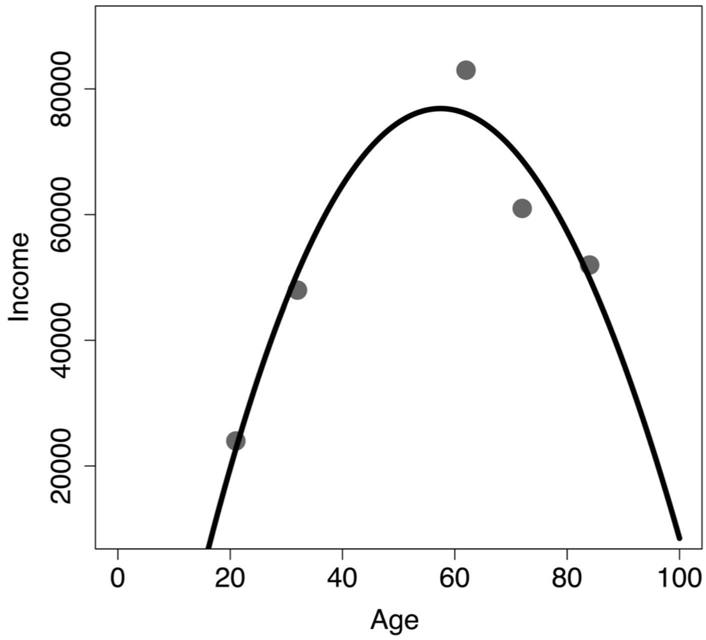
Income
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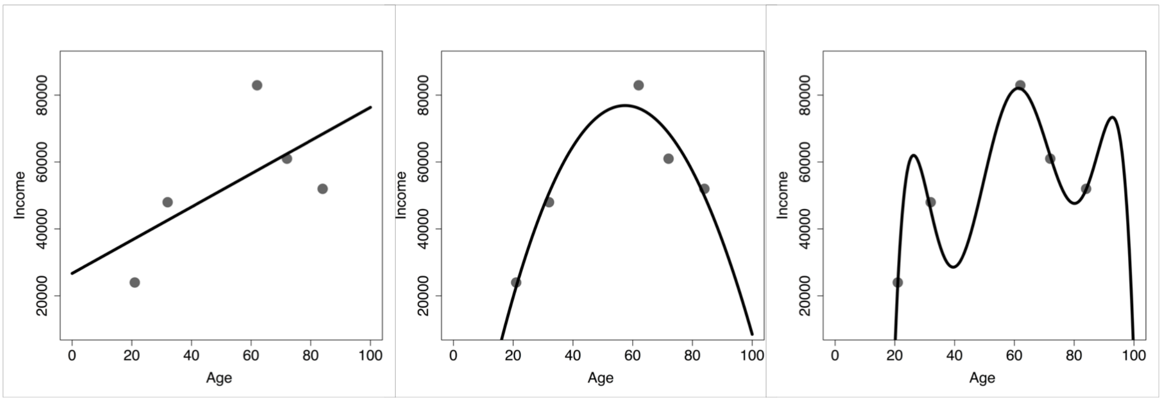
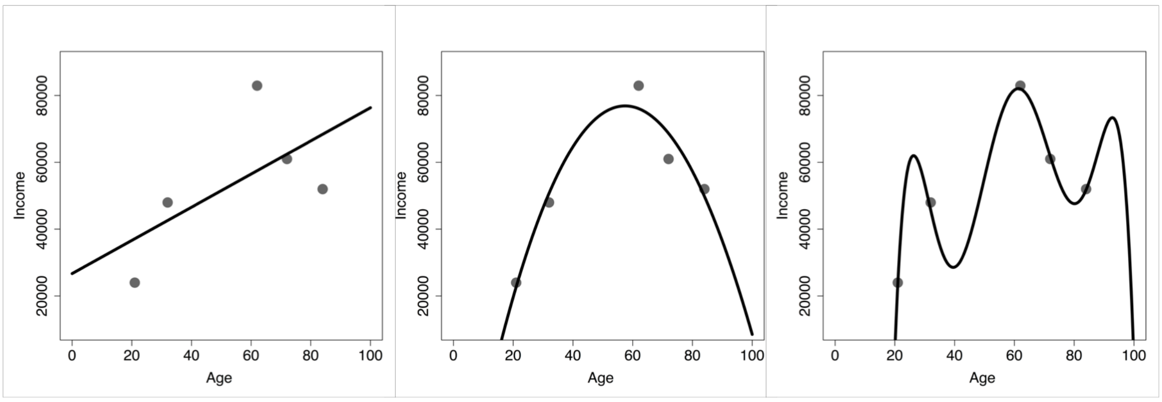
80
100
Age

Underfitting



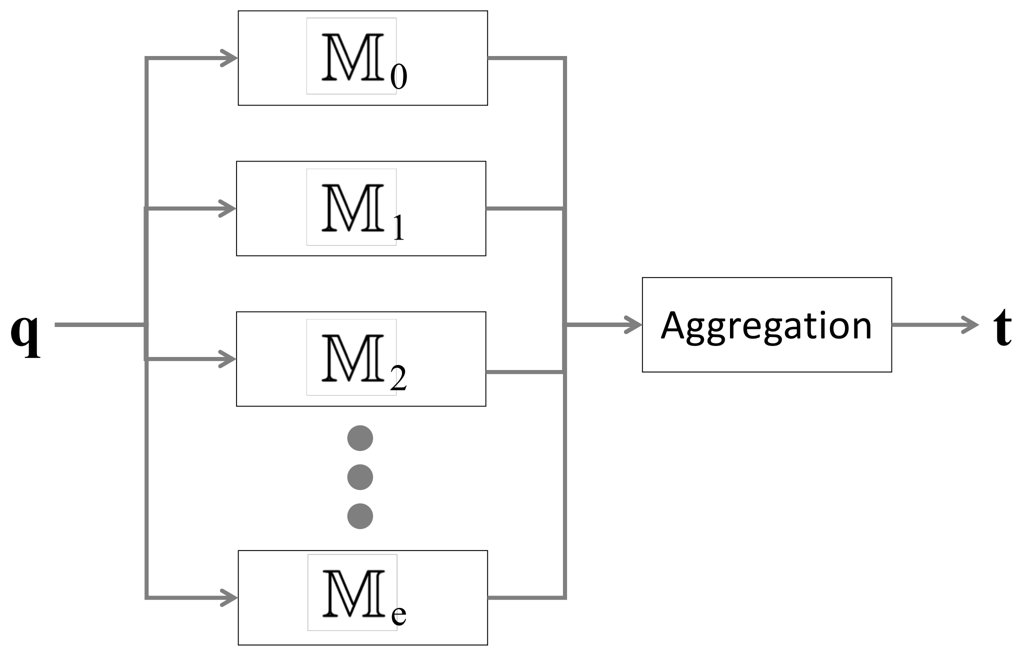
Overfitting

Bias



Variance

ENSEMBLES



Ensembles

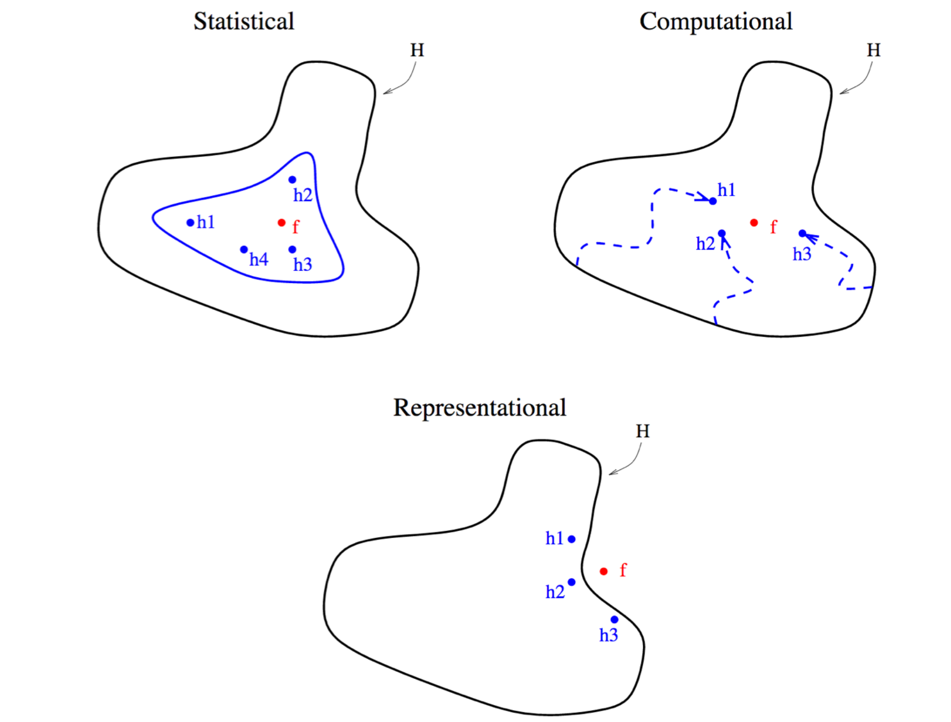
The aggregate of multiple combined models is more effective than any individual model

Thomas Dietterich describes 3 motivations for using ensembles:

- Statistical
- Computational
- Representational

Ensemble Methods in Machine Learning
Thomas G Dietterich
http://web.engr.oregonstate.edu/~tgd/publications/mcs-ensembles.pdf

MAYBE A WISDOM OF THE CROWD EXPERIMENT



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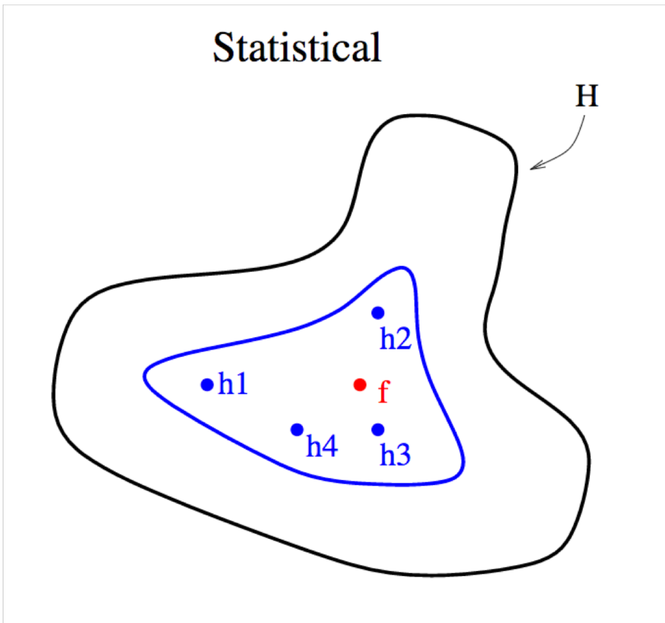

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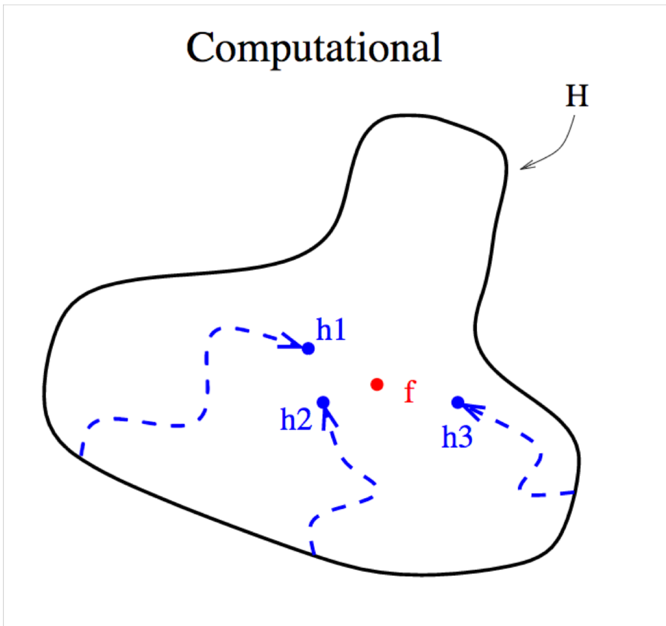

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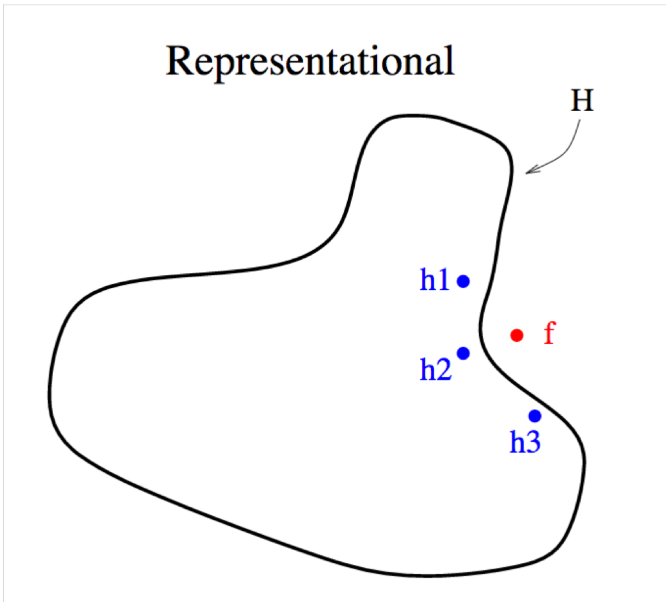

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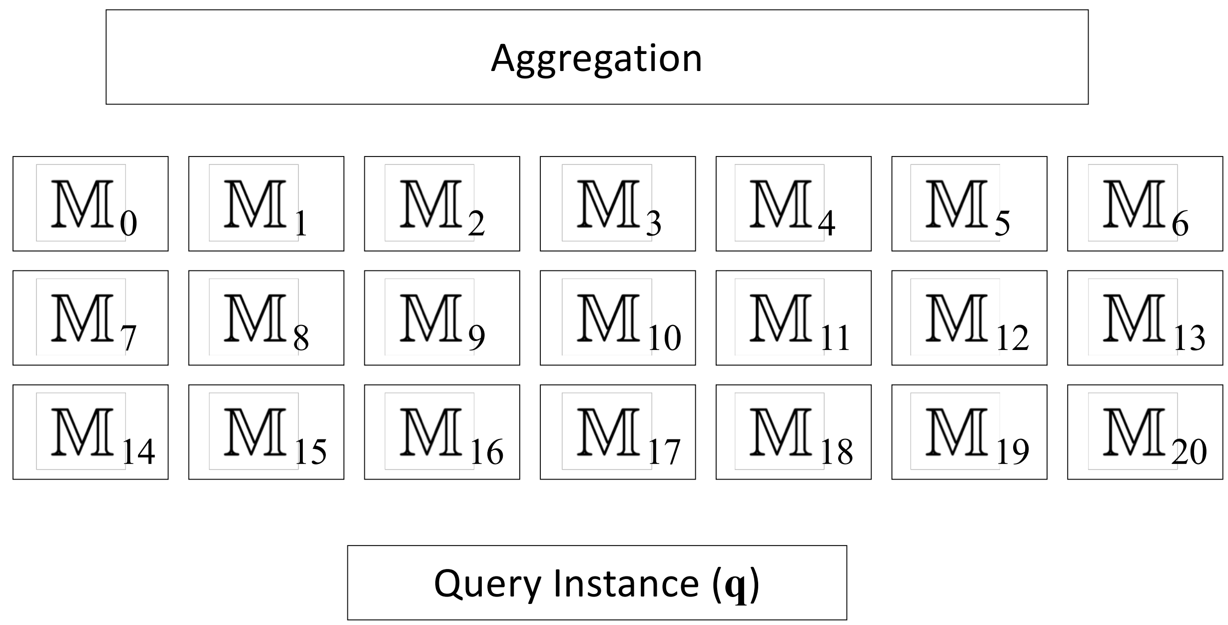
Ensembles

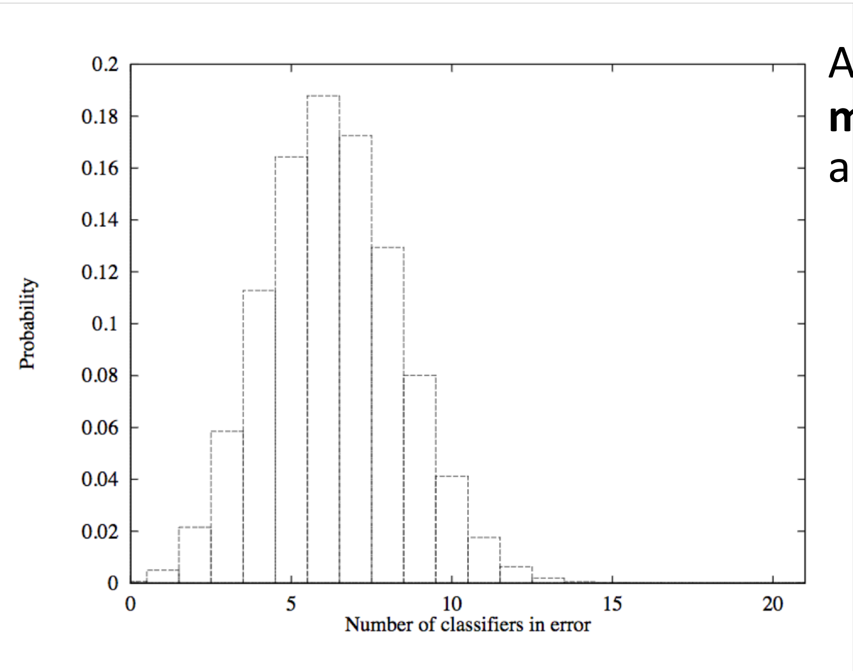
Imagine we have an ensemble for a binary prediction problem with 21 models, each with a classification error of 0.3

The big idea behind ensembles is that if we have multiple learners that are diverse, when one is wrong there is a very good chance that others are correct



Ensembles

More formally if the error rate of each of the L models in an ensemble is less than ½ and if the errors are independent, then the probability that the majority vote of the ensemble will be wrong will be the area under the binomial distribution where more than $L/2$ models are wrong



An ensemble of **21 models** each with an error rate of **0.3**

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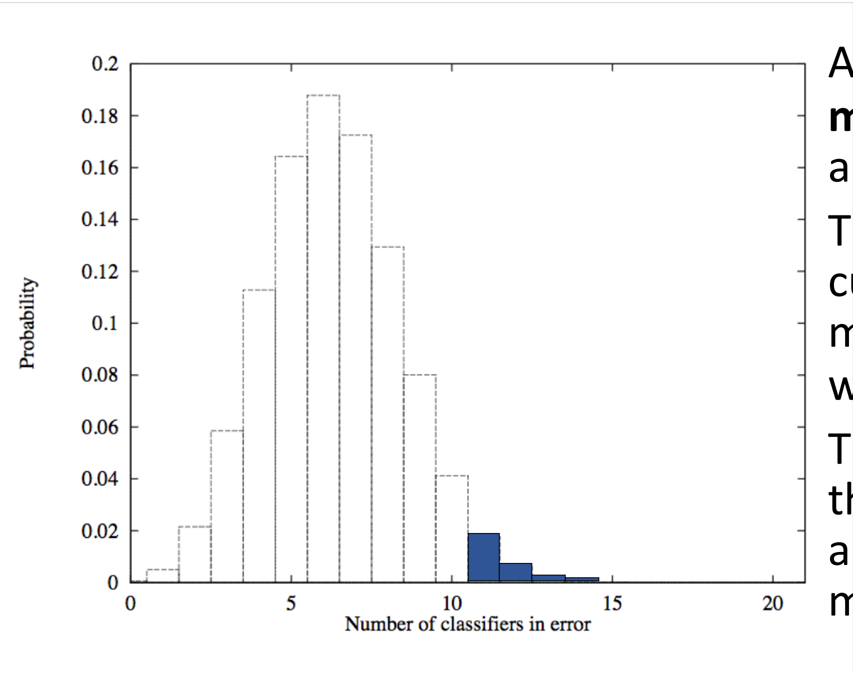


An ensemble of **21 models** each with an error rate of **0.3**

The area under the curve for 11 or more models being wrong is **0.026**

This is much less than the error of any individual model

Ensemble Methods in Machine Learning
Thomas GDietterich
http://web.engr.oregonstate.edu/~tgd/publications/mcs-ensembles.pdf

Ensembles

But models in a real ensemble are never independent so we don't quite do that well

In general we build our ensembles to have two competing characteristics

- Individual models in the ensemble should be strong
- The correlation between the models in the ensemble should be weak (diversity)

Practical Ensembles

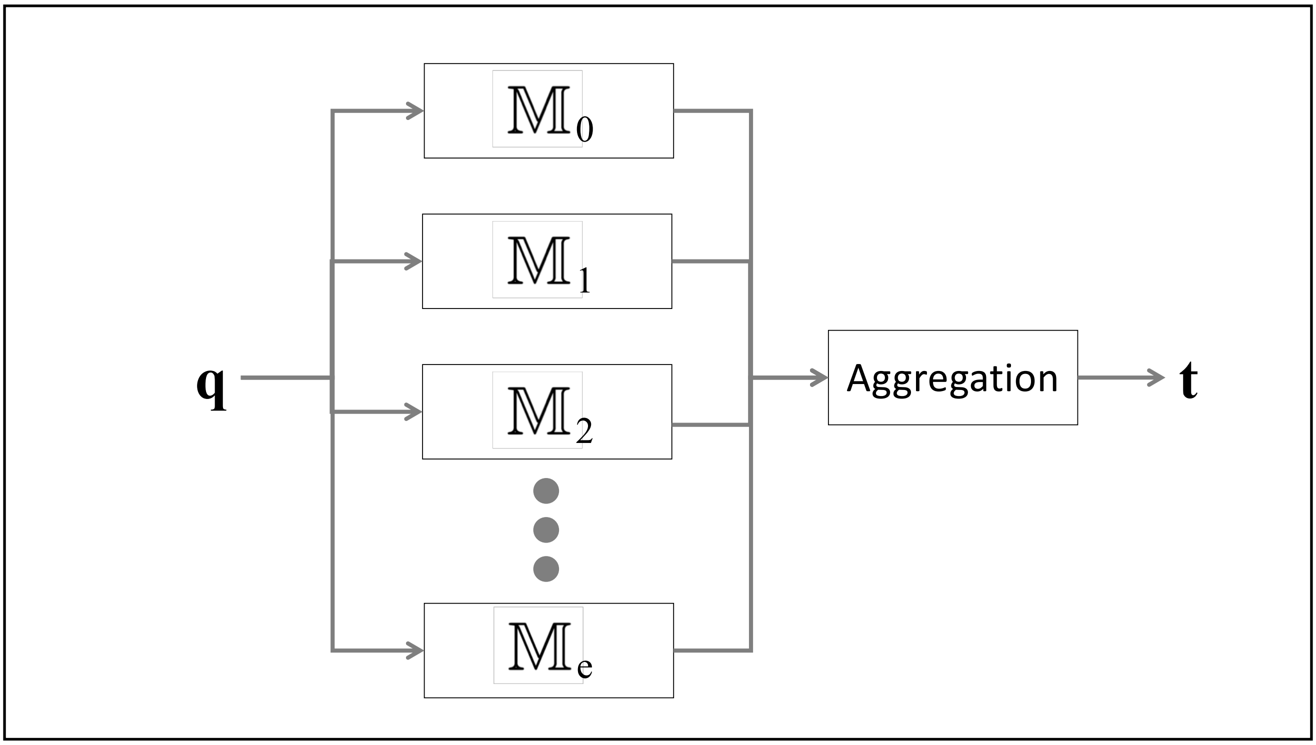
There are however a series of pracical ensemble approaches

- Bagging
- Random forests
- Boosting
- Gradient boosting
- Stacking

Practical Ensembles

There are however a series of pracical ensemble approaches

- **Bagging**
- **Random forests**
- Boosting
- Gradient boosting
- Stacking



Practical Ensembles

In general we would like our ensembles to have two characteristics

- Individual models in the ensemble should be strong
- The correlation between the models in the ensemble should be weak (diversity)

These two characteristics are in tension with each other

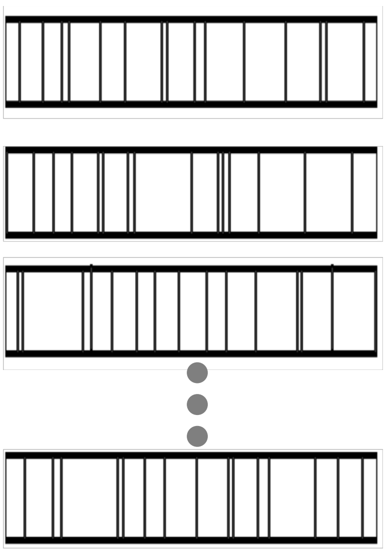
BAGGING

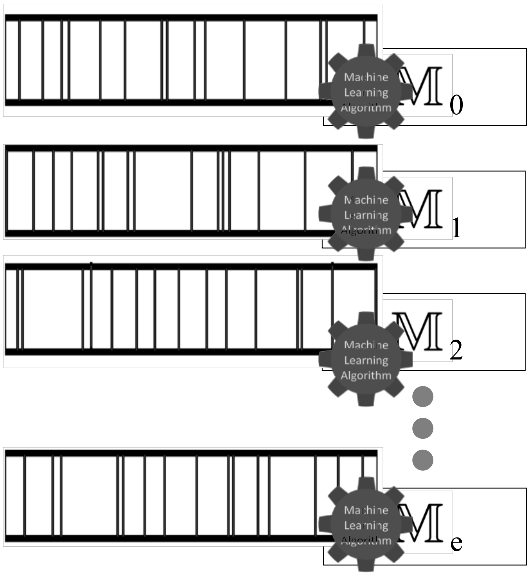
Bagging

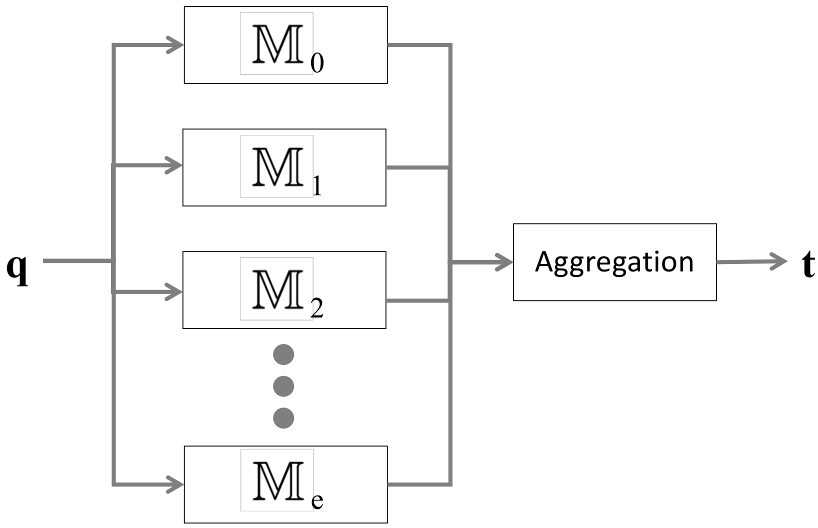
Very simple ensemble training technique

- Trains *e* models in parallel using bootstrapped data samples from an overall training set (100% sampling with replacement)
- Aggregates using majority voting
- *Boostrapped aggregating = bagging*

Breiman, Leo. "Bagging predictors." *Machine learning* 24.2 (1996): 123-140.




Machine Learning Algorithm
M 0
M 1
M 2
M e


q
M 0
M 1
M 2
M e
Aggregation
t

RANDOM FORESTS

Random Forests

Simple but very powerful ensembling technique

- Trains *e* models in parallel using bootstrapped and sub-space sampled data samples from an overall training set
- Aggregates using majority voting

Breiman, Leo. "Random forests." *Machine learning* 45.1 (2001): 5-32.

ID	F1	F2	F3	Target
1	-	-	-	-
2	-	-	-	-
3	-	-	-	-
4	-	-	-	-

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ID	F1	F2	F3	Target
1	-	-	-	-
2	-	-	-	-
3	-	-	-	-
4	-	-	-	-

Bagging and Subspace Sampling

ID	F1	F3	Target
1	-	-	-
1	-	-	-
2	-	-	-
3	-	-	-

ID	F2	F3	Target
2	-	-	-
2	-	-	-
4	-	-	-
4	-	-	-

ID	F1	F3	Target
1	-	-	-
3	-	-	-
3	-	-	-
4	-	-	-

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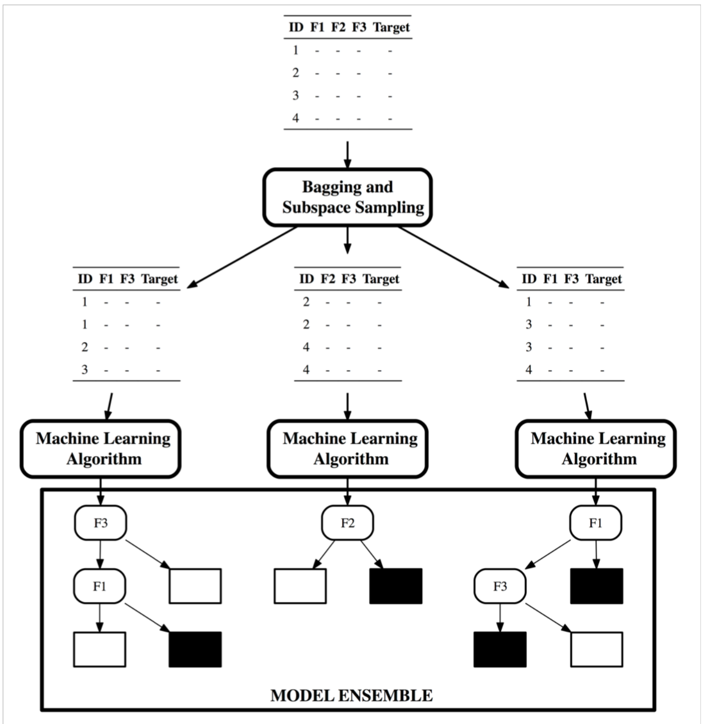

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SUMMARY

Summary

- Supervised learning involves bulding prediction models that learn patterns between a set of descriptive fetaures and a target feature based on a large labelled dataset
- Training a model can be viewed as a search process
- Inductive bias is required for this search process to converge

Summary

- Ensembles are amongst the most powerful supervised learning techniques
- Random forests, in particular, are very simple but very effective

Questions

?