Machine Learning 2: Optimisation and good practices

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- Regularisation

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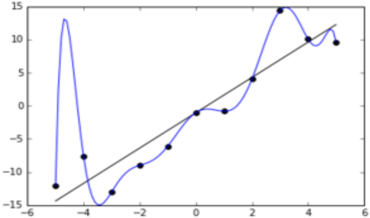

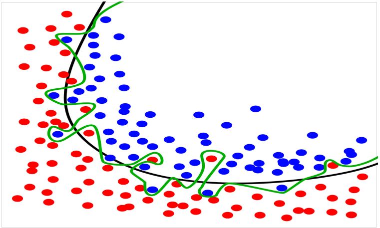

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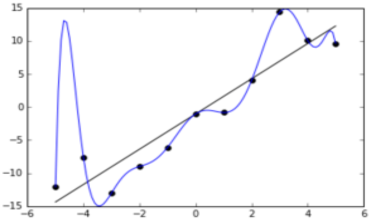

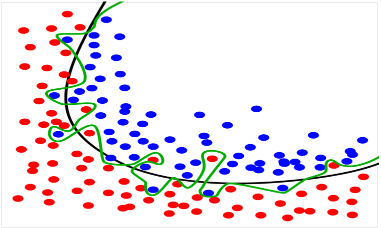

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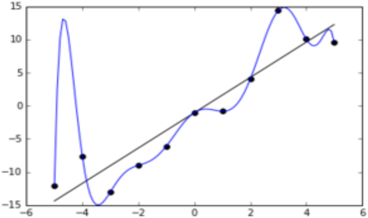

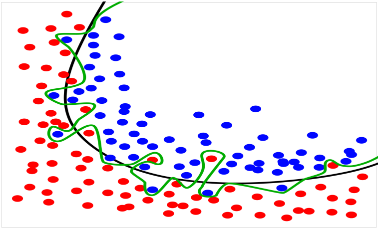

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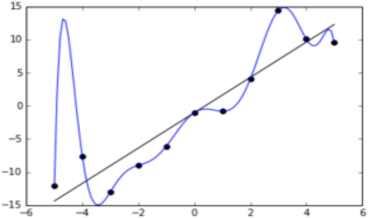

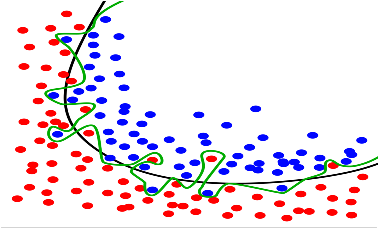

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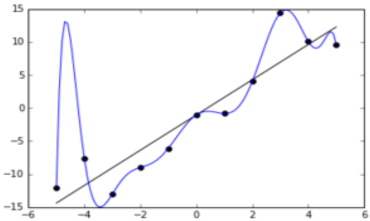

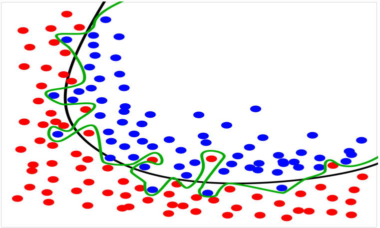

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Options to cure overfitting/ high variance:

1. Reduce number of features .... manually ??, use some model selection algorithm ??
2. Incorporate a method that 'weights' features in order of their importance — **regularisation**.

Regularisation can just be added as a term in the cost function ....

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m}\left[y^i \log[h(\theta^{\mathsf{T}}\mathrm{x}^{\mathrm{i}})] + (1-y^i)\log[1-h(\theta^{\mathsf{T}}\mathrm{x}^{\mathrm{i}})]\right] + \lambda\theta^T\theta.$$

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How do we choose value in practice?

Cross-validation and test sets

[1] done w/o regularisation!

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How do we test a given ML algorithm or choice of λ ?

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1. Split data roughly into three sets:
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4. Calculate the error on the test set to confirm choice.

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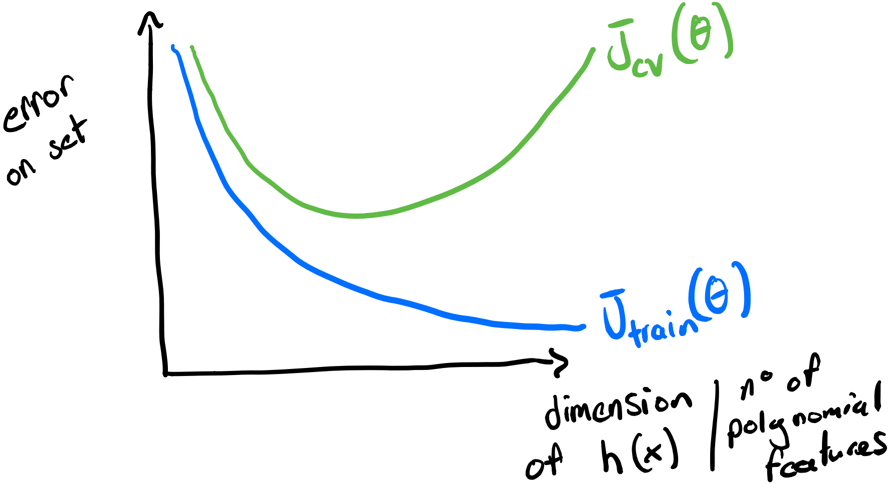
Diagnosing bias and variance - dimension



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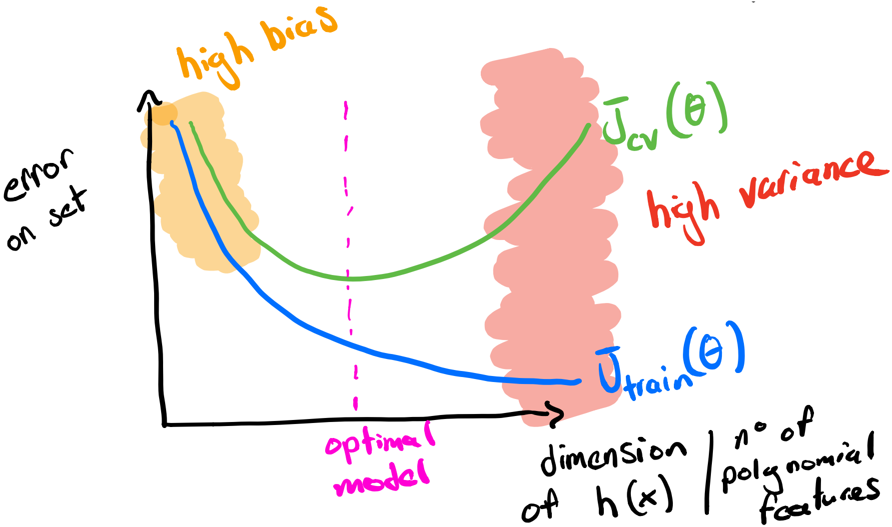

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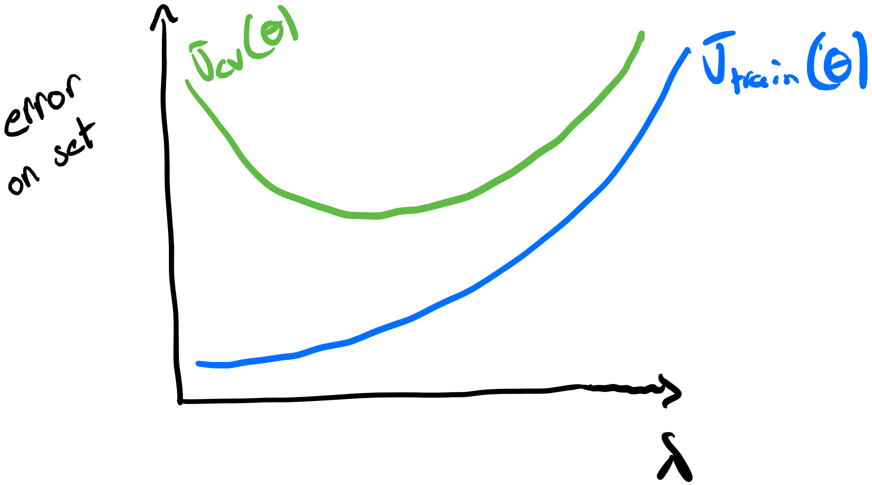

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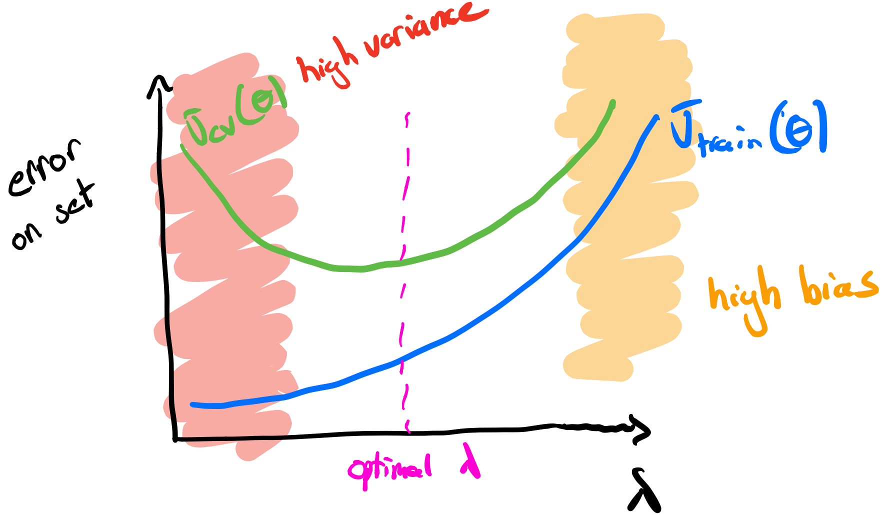

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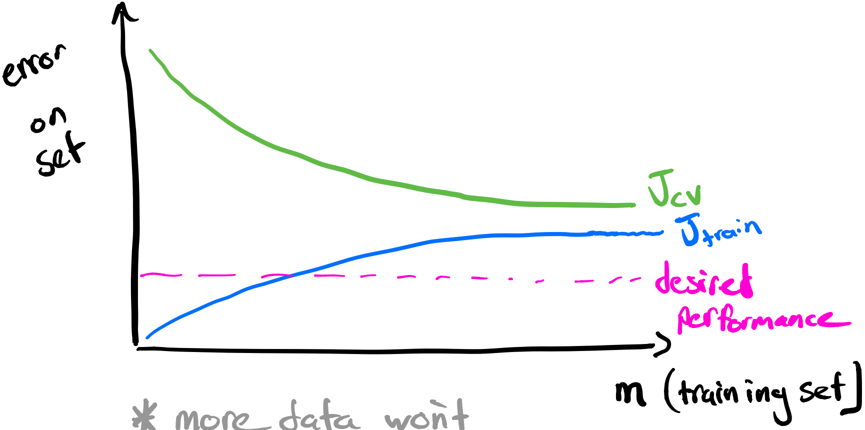

* more data won't generally help → asymptotic

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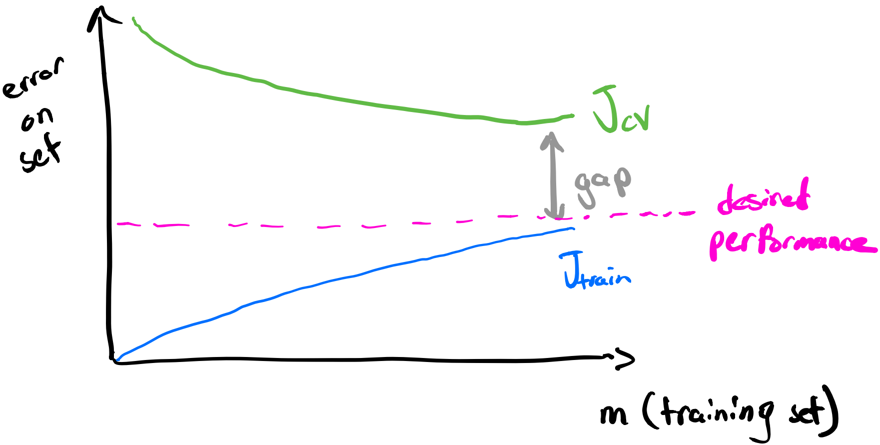

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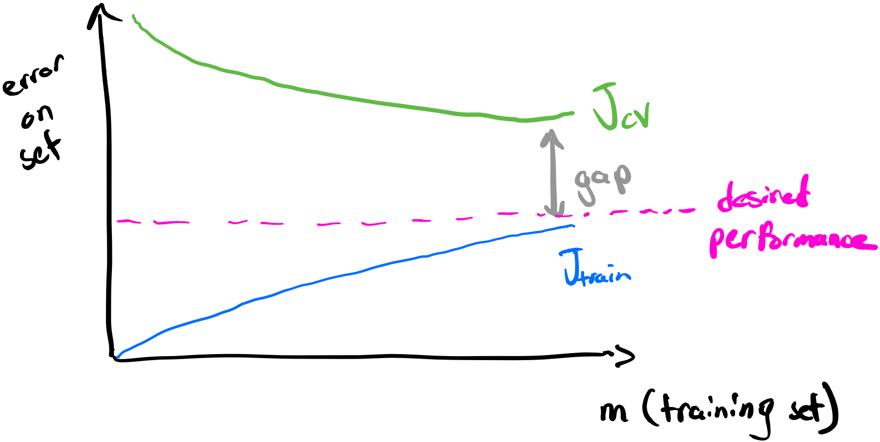

See python example 2

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How to approach an ML problem?

1. Take a look at your data and pre-process them
2. Quick and dirty algorithm to get some predictions.
3. Plot learning curves to inspire accuracy improvement.
4. Error analysis — **requires a well defined error-metric!**

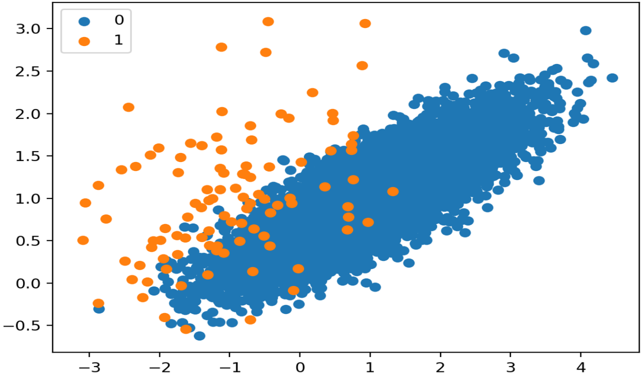
One can use the obvious metric :

$$Error = \frac{1}{m_{set}} \sum_{i=1}^{m_{set}} err(h(\theta^T x^i), y^i), \tag{2}$$

where

$$err(h(\theta^T x^i), y^i) = \begin{cases} 1 & h(\theta^T x^i)_{y=0} \ \geq 0.5 \quad OR \quad h(\theta^T x^i)_{y=1} \ < 0.5 \\ 0 & \text{otherwise} \end{cases},$$

Skewed data



Setting $h(\theta^T x) = 0$ always will give a very low error....

Precision and Recall

		Actual	
		1	0
Predicted	1	True positive	False positive
	0	False negative	True negative

$$Precision = \frac{\text{True Pos}}{\text{True Pos} + \text{False Pos}}, \qquad Recall = \frac{\text{True Pos}}{\text{True Pos} + \text{False Neg}} \tag{3}$$

Note: Set rarest class to be $y = 1$!

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- We can change the threshold, $h(\theta^T x) \geq \textit{threshold}$, such that we gain or lose precision or recall.
- The higher the threshold the higher the precision but the lower the recall.
- One can combine the two into the **F-score** which we try to maximise

$$0 \leq F_1 = \frac{2PR}{P+R} \leq 1 \tag{4}$$