Machine Learning 2: Optimisation and good practices

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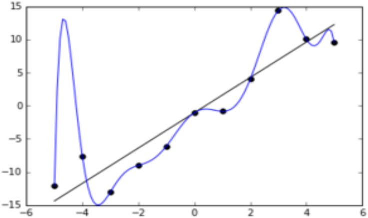

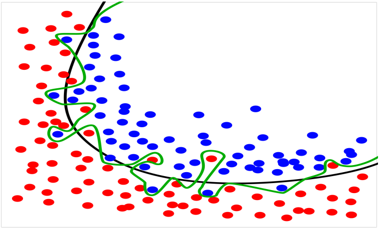

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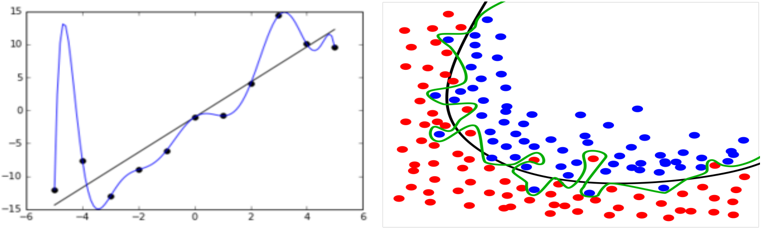

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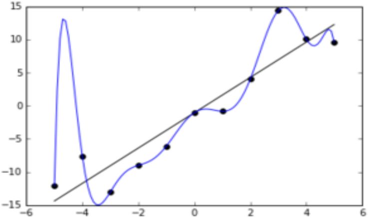

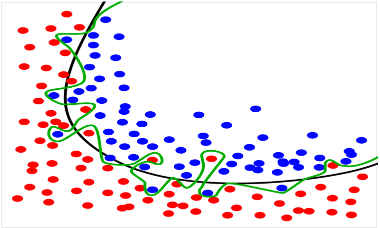

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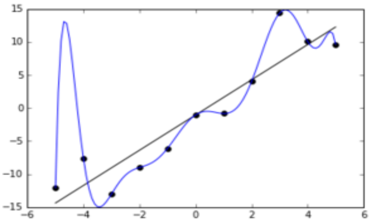

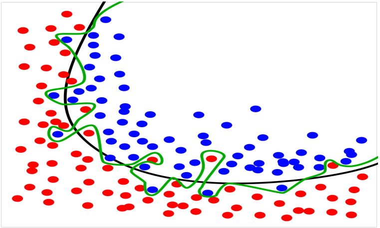

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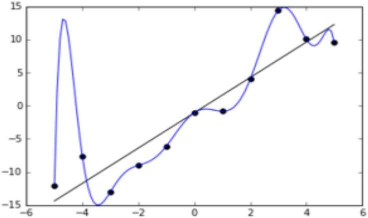

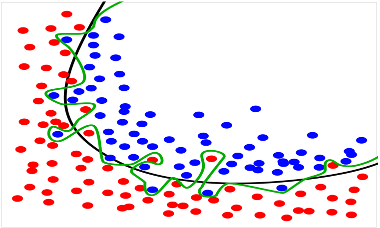

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2. Incorporate a method that 'weights' features in order of their importance — **regularisation**.

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

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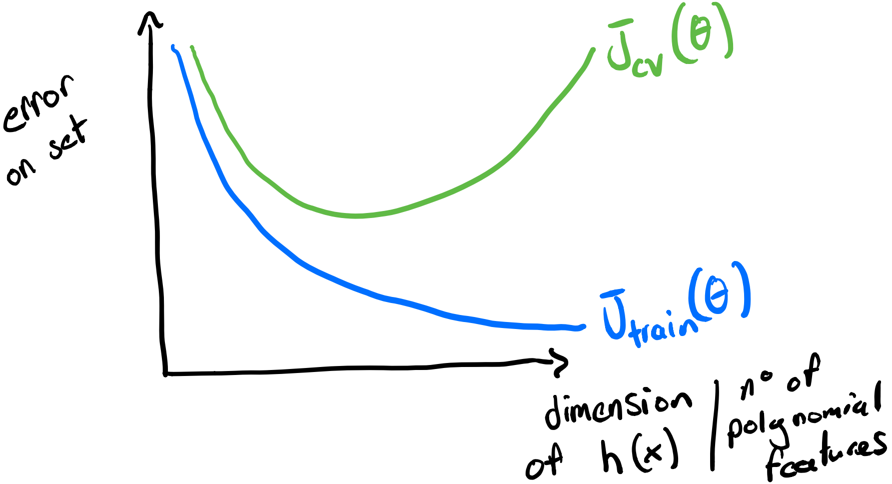
4. Calculate the error on the test set to confirm choice.

Diagnosing bias and variance - dimension



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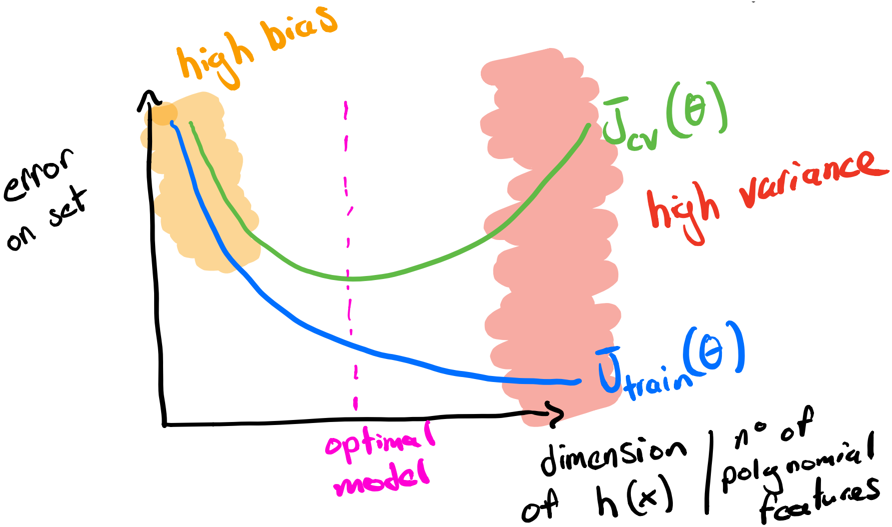

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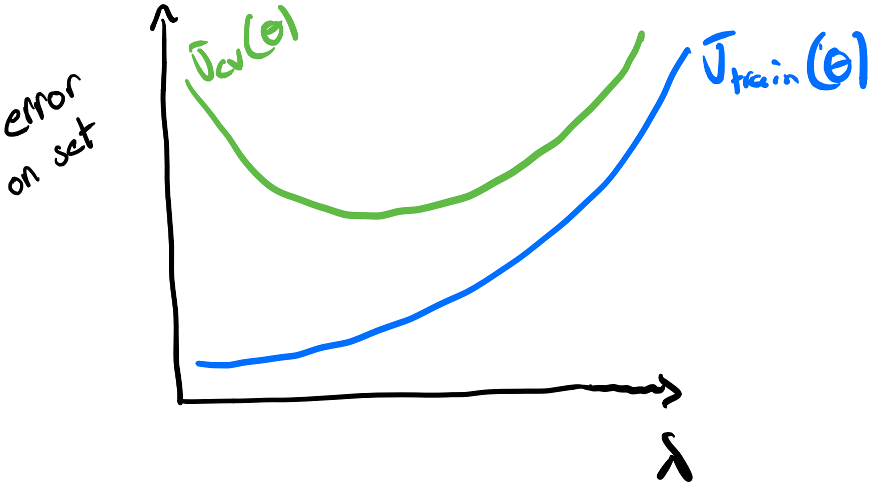

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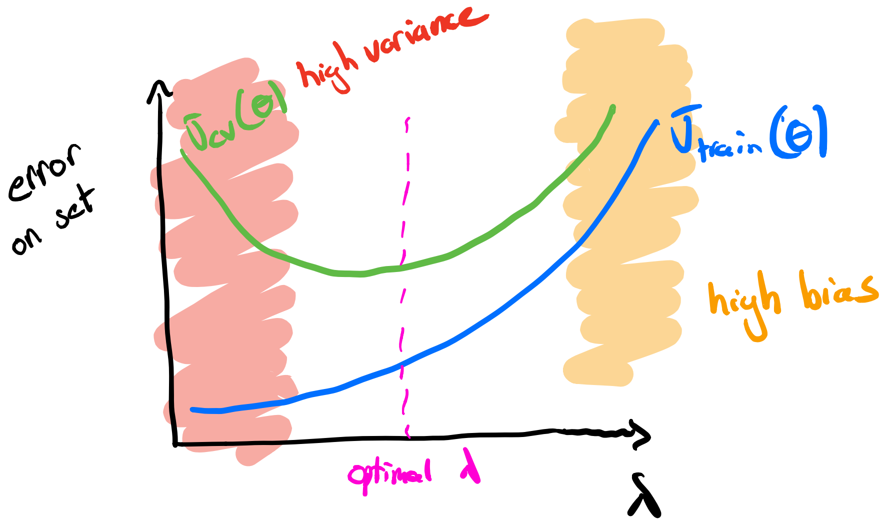

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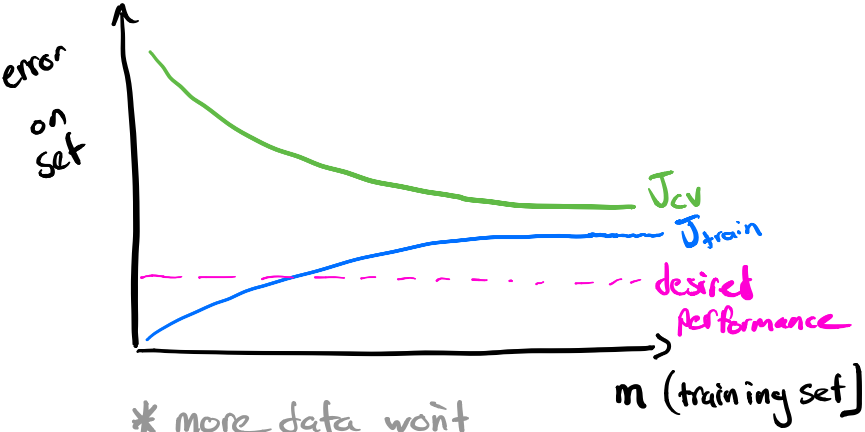

* more data won't generally help → asymptotic.

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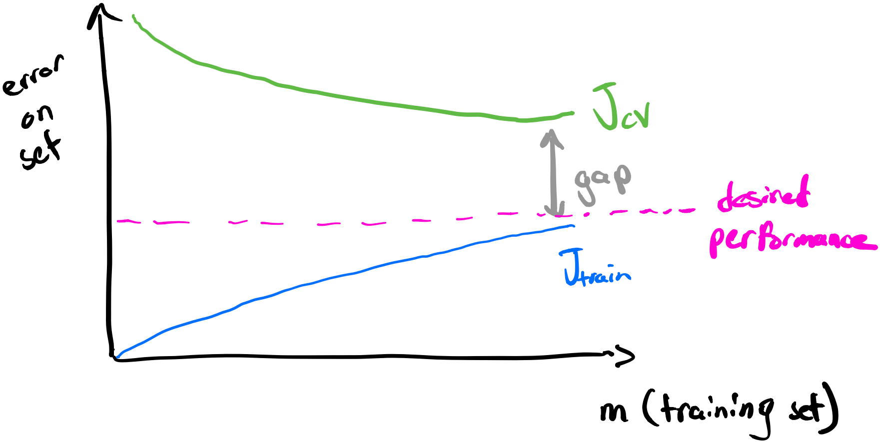

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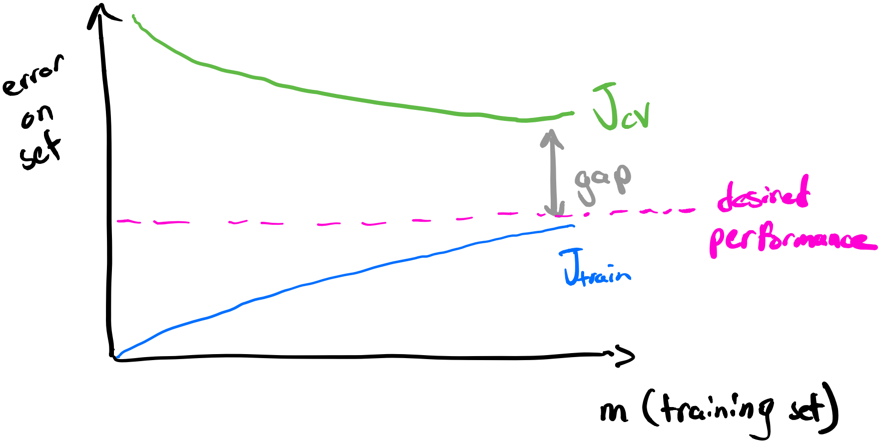

See python example 2

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How to approach an ML problem?

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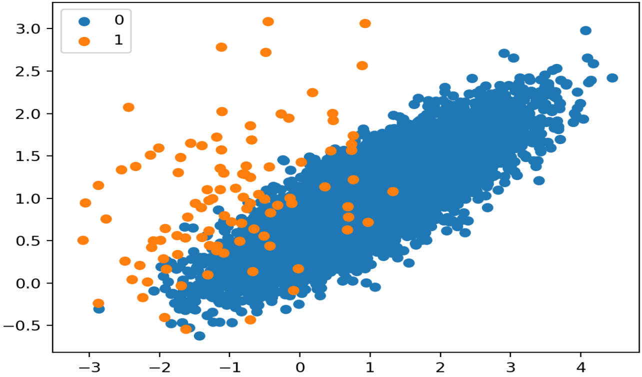
One can use the obvious metric :

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

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

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

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

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Some notes:

- We can change the threshold, $h(\theta^T x) \geq threshold$, such that we gain or lose precision or recall.

Precision and Recall

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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

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