

What does overfitting look like?

- validation set MSE higher than train set MSE
- validation set accuracy lower than ~~validation~~ train set accuracy
- regression: predictions not smooth enough - fitting noise, not trend
- classification: decision boundary not smooth enough - fitting noise, not trend

Later layers have more complex activations

~~Factors~~ we have available to address overfitting:

Tools

- # layers, # units per layer
- Weight regularization
- Drop out

Process for finding a model:

- 1) Read the literature or find examples from a similar setting or application
- 2) Choose your best guess at a good starting point. Fit to training data & evaluate on validation data.
- 3) Increase model capacity until you are overfitting
- 4) Regularize model
 - Add L1 or L2 regularization
 - Add drop out
 - Remove layers / units
 - Reduce # of epochs (early stopping)

Can also tune things like learning rate, which optimizer you are using.

- 5) Refit to combined training & validation data and evaluate on test set.

L2 regularization in terms of gradient calculations:

$$J(b, w) = \frac{1}{m} \sum_{i=1}^m J^{(i)}(b, w) + \sum_{l=1}^L \lambda^{[l]} \|w^{[l]}\|_2^2$$

stands for $\sum_i \sum_j (w_{ij}^{[l]})^2$

$$\frac{\partial}{\partial w^{[l]}} J(b, w) = (\text{stuff from backpropagation}) + \lambda^{[l]} \cdot 2 \cdot w^{[l]}$$

matrix of same shape as $w^{[l]}$ (n_{l-1}, n_l) where entry i, j is

$$\frac{\partial J(b, w)}{\partial w_{ij}^{[l]}}$$

because $\frac{\partial}{\partial w_{ij}^{[l]}} \sum_{l=1}^L \lambda^{[l]} \sum_i \sum_j (w_{ij}^{[l]})^2 = 2 \lambda^{[l]} w_{ij}^{[l]}$

So a gradient descent update step looks like:

$$w^{[l]} = w^{[l]} - \text{learning-rate} * (\text{stuff from backpropagation} + 2 \lambda w^{[l]})$$

$$= w^{[l]} (1 - 2 \lambda * \text{learning-rate}) - \text{learning-rate} * (\text{stuff from backpropagation})$$

every gradient descent step tries to shrink weights towards 0 (unless offset by a gradient term)