

CS 171: Intro to ML and DM

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UC Riverside

Slide Set 5: Cross Validation



- From UC Riverside

- ▶ CS 171: Introduction to Machine Learning and Data Mining
- ▶ Professor Christian Shelton

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 - ▶ Elements of Statistical Learning (Hastie, et al.)
 - ▶ Pattern Recognition and Machine Learning (Bishop)
 - ▶ An Introduction to Machine Learning (Kubat)
 - ▶ Machine Learning: A Probabilistic Perspective (Murphy)
- ▶ For use only by enrolled students in the course

Cross-Validation for Regularization

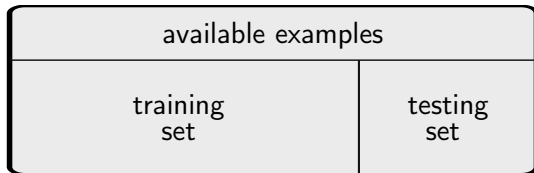
So, how to pick λ ?

Cross-Validation for Regularization

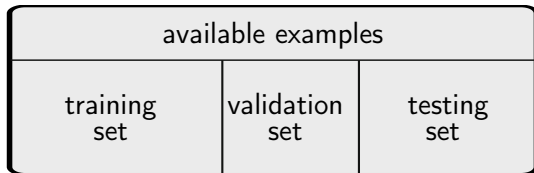
So, how to pick λ ?

Cross validation! (or n -fold cross validation)

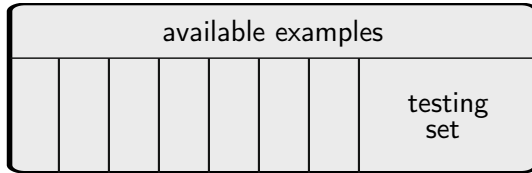
Cross Validation



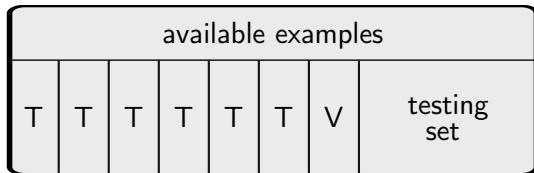
Cross Validation



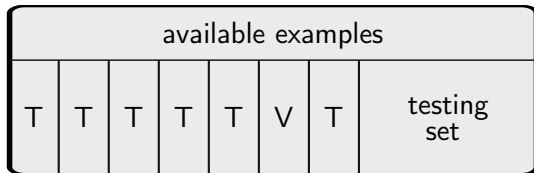
Cross Validation



Cross Validation



Cross Validation



Cross Validation

available examples							
T	T	T	T	V	T	T	testing set

Cross Validation

available examples							
T	T	T	V	T	T	T	testing set

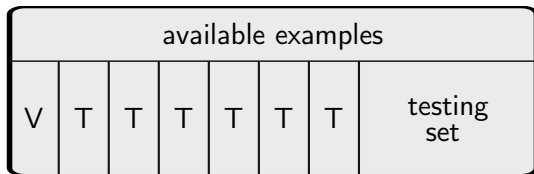
Cross Validation

available examples							
T	T	V	T	T	T	T	testing set

Cross Validation

available examples							
T	V	T	T	T	T	T	testing set

Cross Validation



Cross Validation:

- Split Training data into two parts: Train and Validation
- For each version (different k), train on train and check performance on validate
- Pick the version that does best on validation set

n -fold Cross Validation:

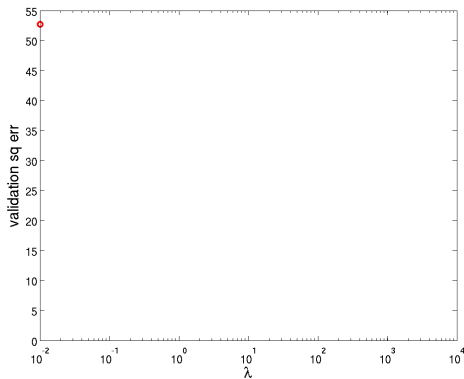
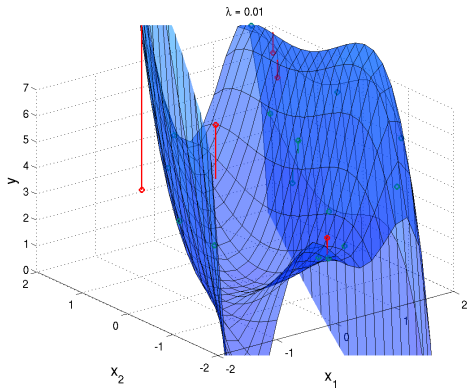
- Do cross validation n times (n different train/validation splits)
- Pick version (value of k) that does best on average across these n different trails
- Most common: partition data into n equal-sized sets and use each one as validation once (and other $n - 1$ sets as train)

Leave-one-out Cross Validation (LOO CV):

- n -fold Cross Validation where $n = m$

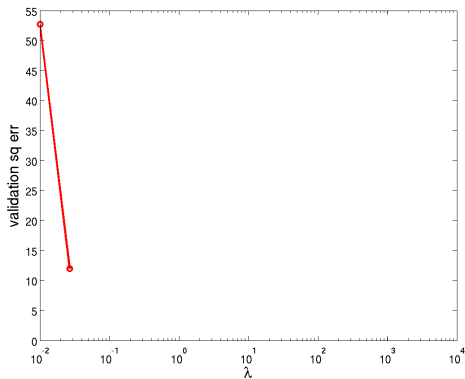
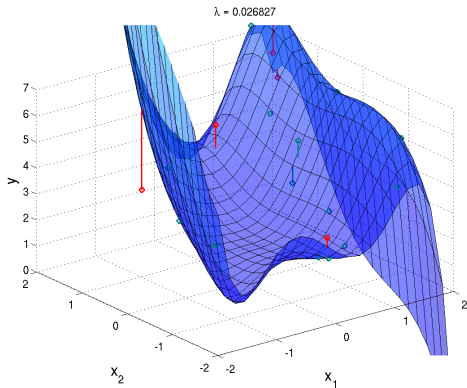
Cross-Validation for Regularization

5th order polynomial



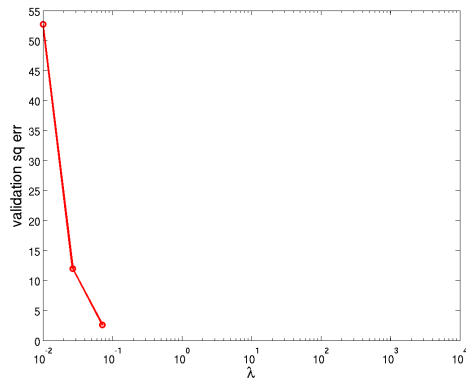
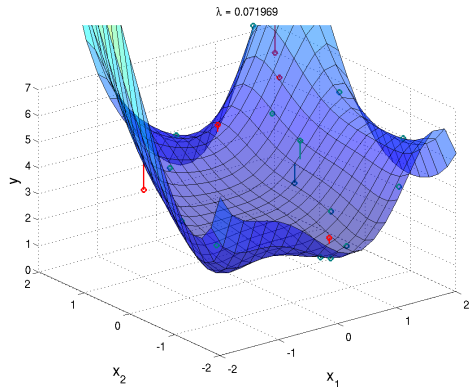
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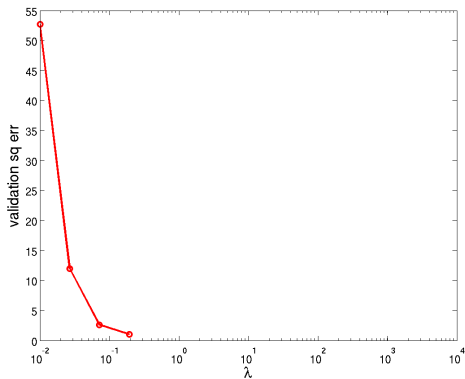
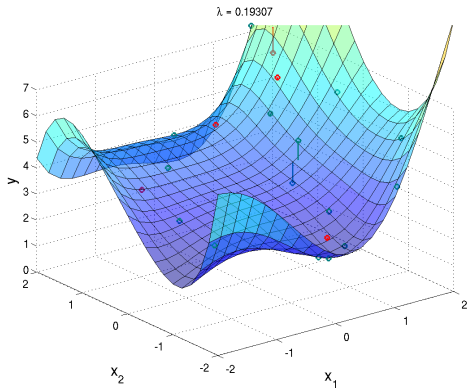
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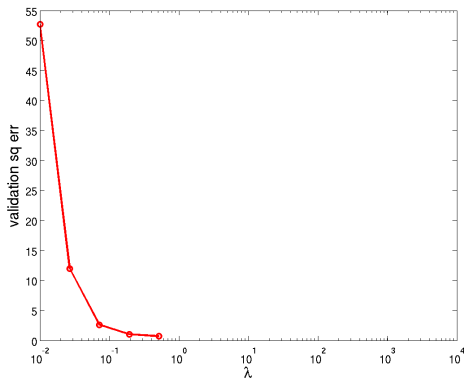
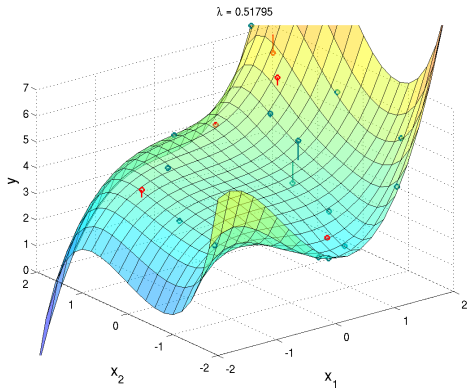
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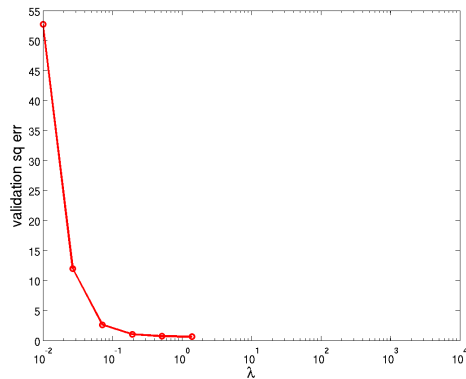
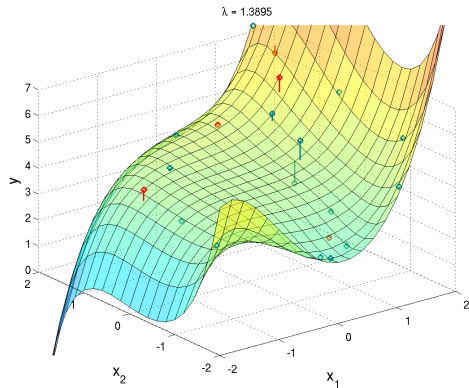
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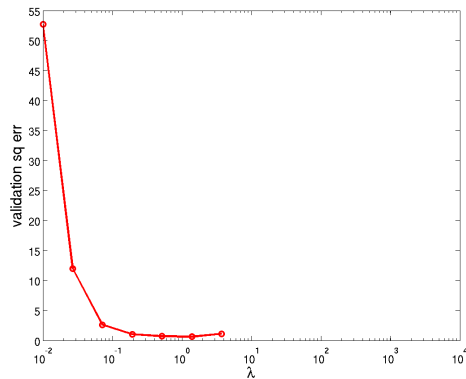
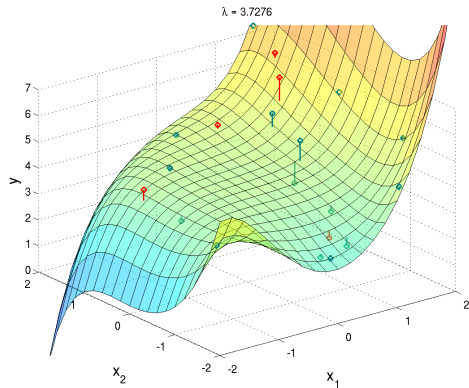
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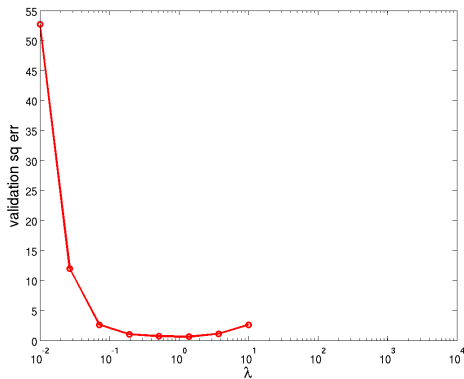
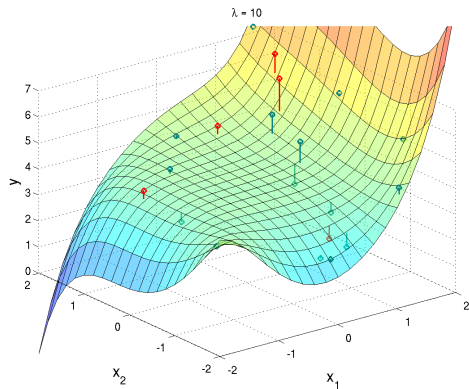
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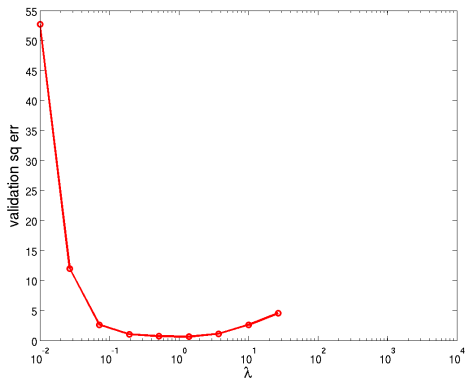
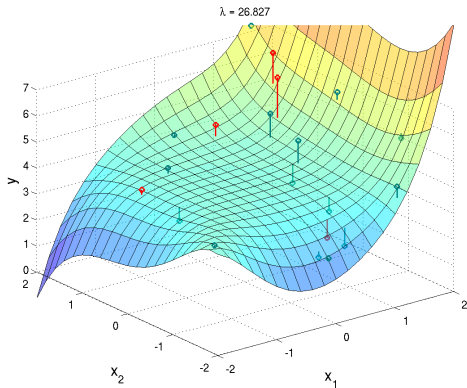
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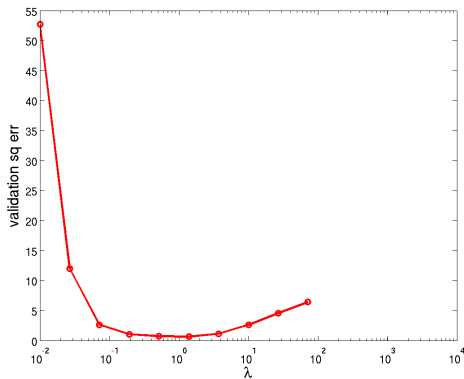
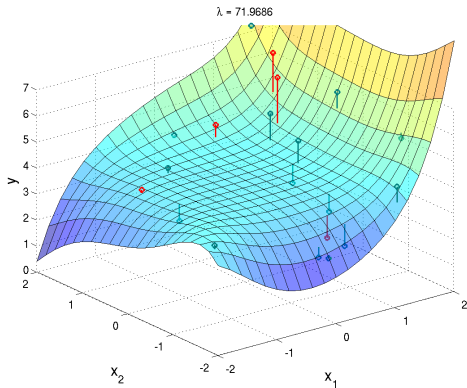
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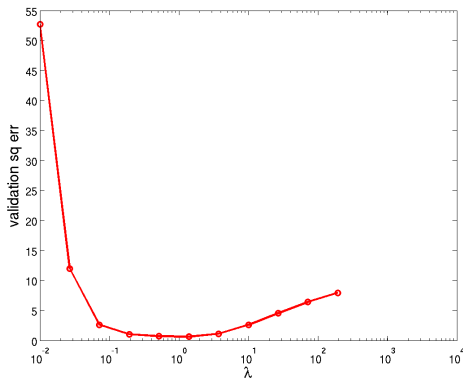
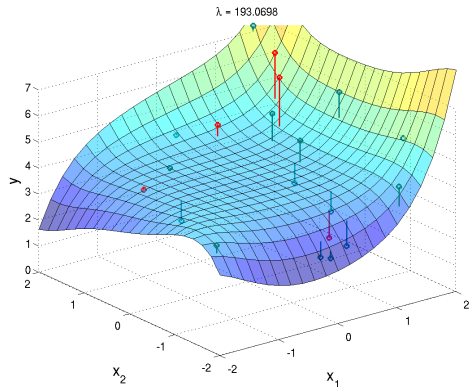
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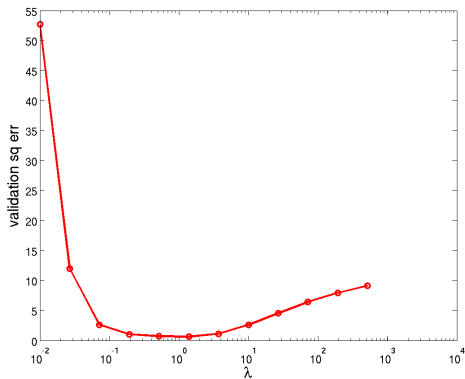
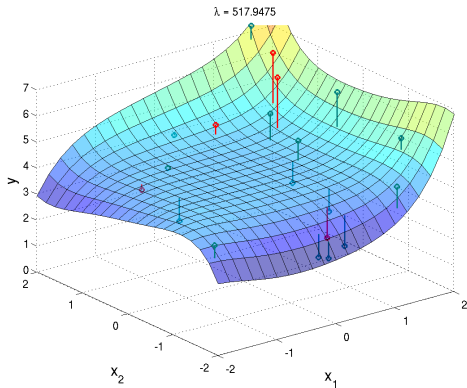
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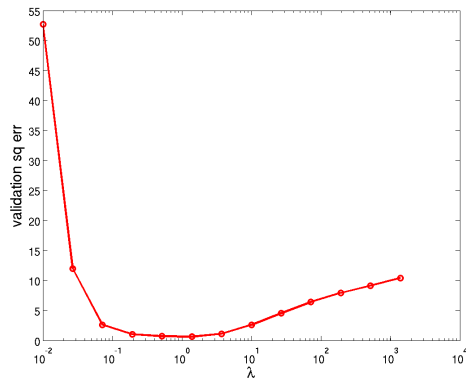
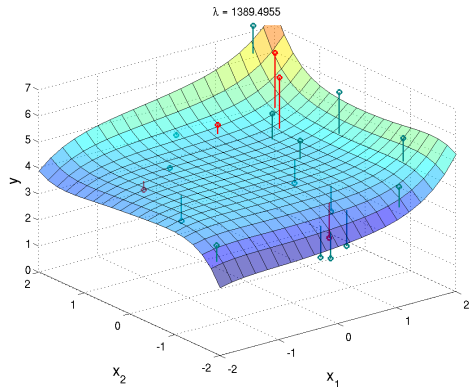
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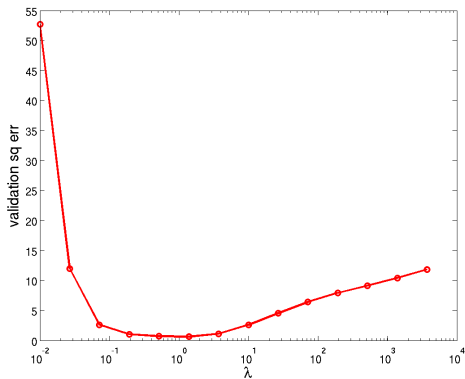
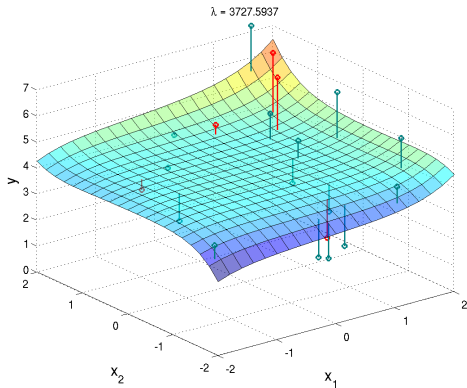
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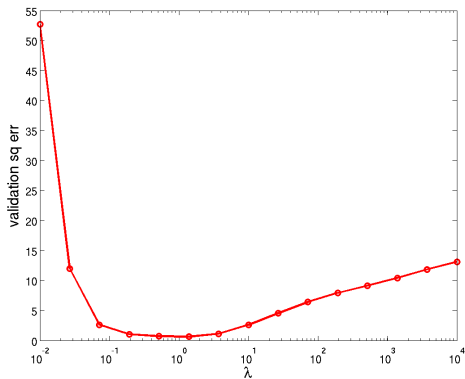
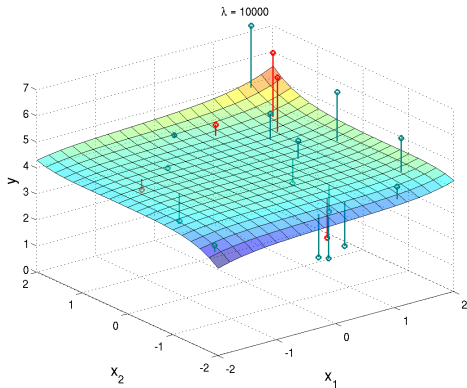
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Regularized Least Squares

Algorithm Development:

- Pick form of function to be estimated:

$$f(x) = w^\top x$$

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 - ▶ Train on Training set using λ
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- (Optional) Retrain on Training+Validation with best λ
- Report best w
- (If testing) Check average per-item loss on Testing set