Supervised learning: training sets, testing sets, overfitting, correlation versus cause and effect, cross-validation, learning curve, inductive bias

Relevant Readings: None

CS495 - Machine Learning, Fall 2009

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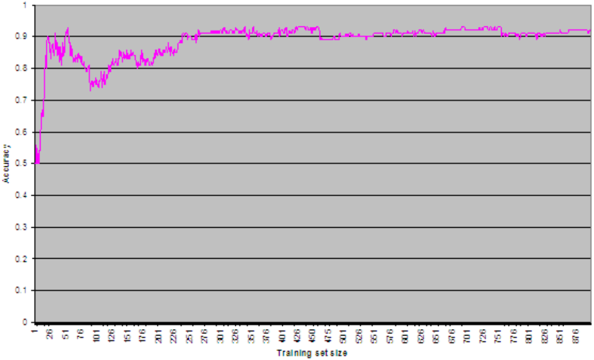

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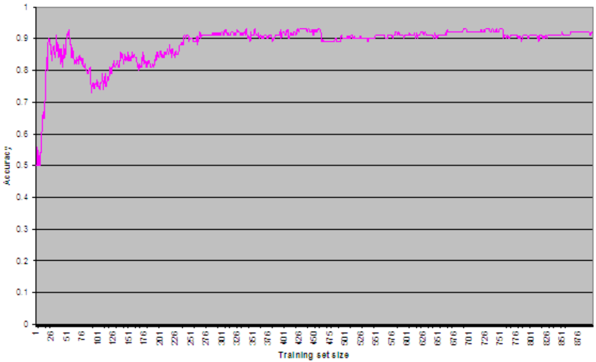

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