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- Note: Feature Selection is different from Feature Extraction
  - The latter transforms original features to get a small set of new features
  - More on feature extraction when we cover **Dimensionality Reduction**

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  - Requires repeated runs of the learning algorithm with different set of features
  - Can be computationally expensive

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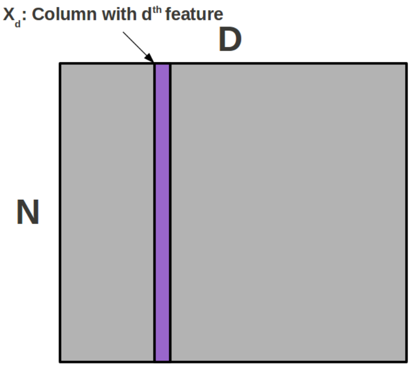

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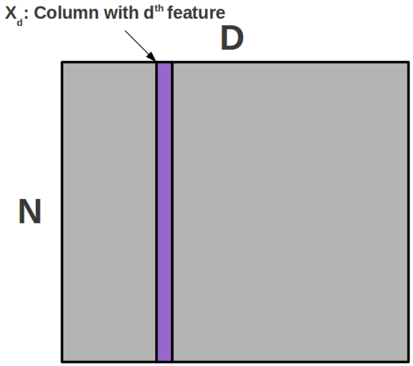

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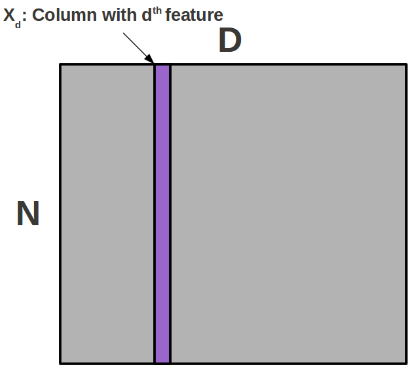

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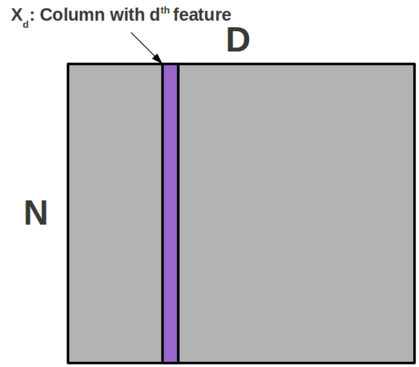

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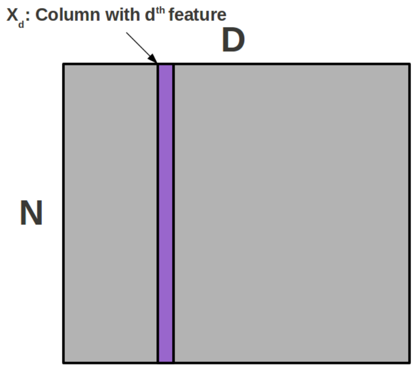

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  - Note: These probabilities can be easily estimated from the data

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  - Inclusion/Removal criteria uses cross-validation

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