Data preprocessing and Data Augmentation

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Data transformations

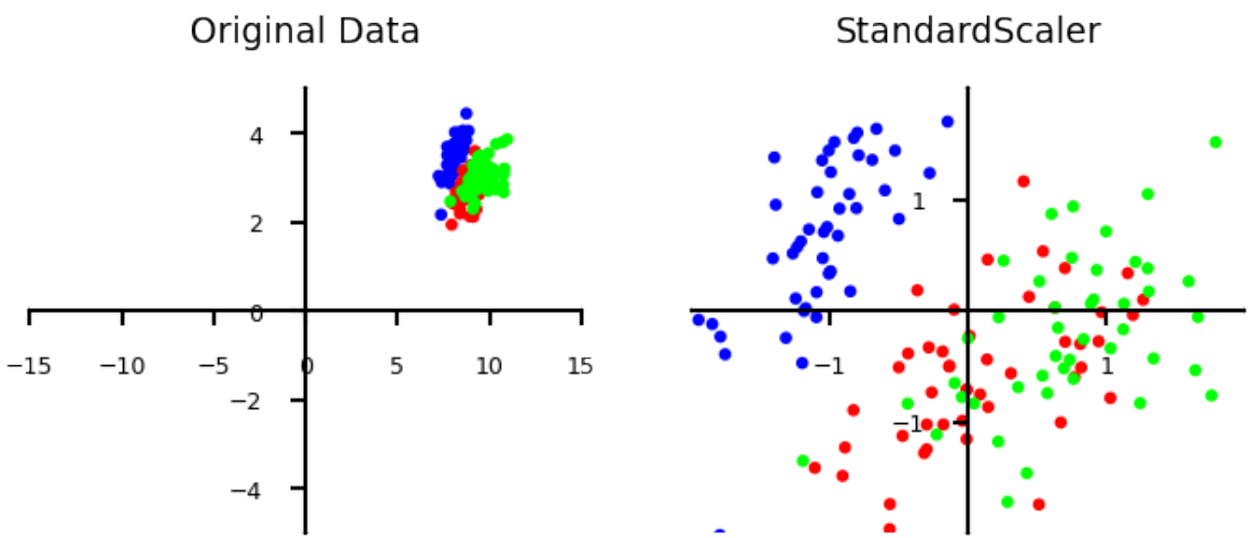
- Machine learning models make a lot of assumptions about the data
- In reality, these assumptions are often violated
- We build pipelines that transform the data before feeding it to the learners
  - Scaling (or other numeric transformations)
  - Encoding (convert categorical features into numerical ones)
  - Automatic feature selection
  - Feature engineering (e.g. binning, polynomial features,...)
  - Handling missing data
  - Handling imbalanced data
  - Dimensionality reduction (e.g. PCA)
  - Learned embeddings (e.g. for text)
- Seek the best combinations of transformations and learning methods

Data transformations (cont.)

- Often done empirically, using cross-validation
- Make sure that there is no data leakage during this process!

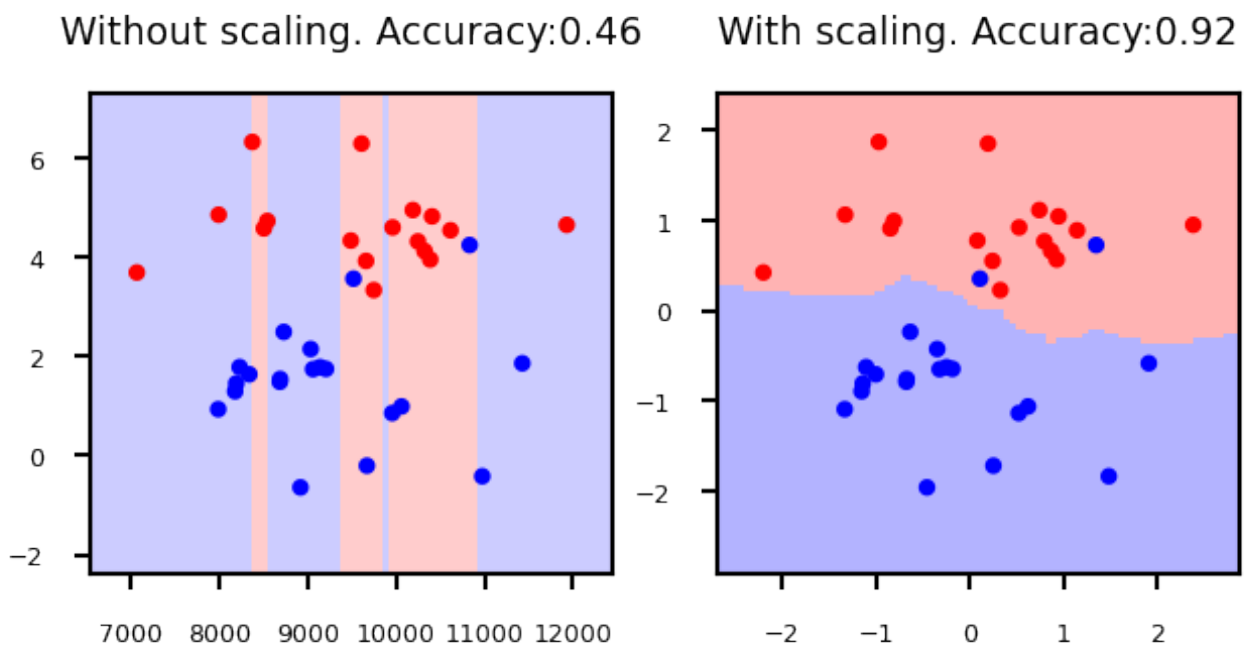
Scaling

- Use when different numeric features have different scales (different range of values)
  - Features with much higher values may overpower the others
- Goal: bring them all within the same range
- Different methods exist



Why do we need scaling?

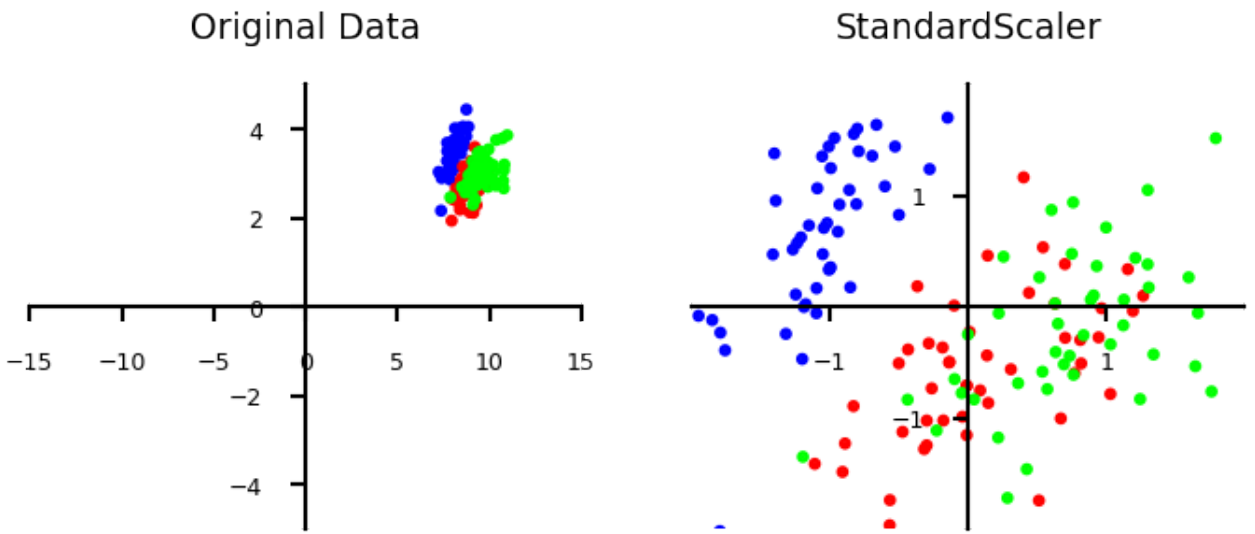
- KNN: Distances depend mainly on feature with larger values
- SVMs: (kernelized) dot products are also based on distances
- Linear model: Feature scale affects regularization
  - Weights have similar scales, more interpretable



Standard scaling (standardization)

- Generally most useful, assumes data is more or less normally distributed
- Per feature, subtract the mean value μ, scale by standard deviation σ
- New feature has $\mu = 0$ and $\sigma = 1$, values can still be arbitrarily large

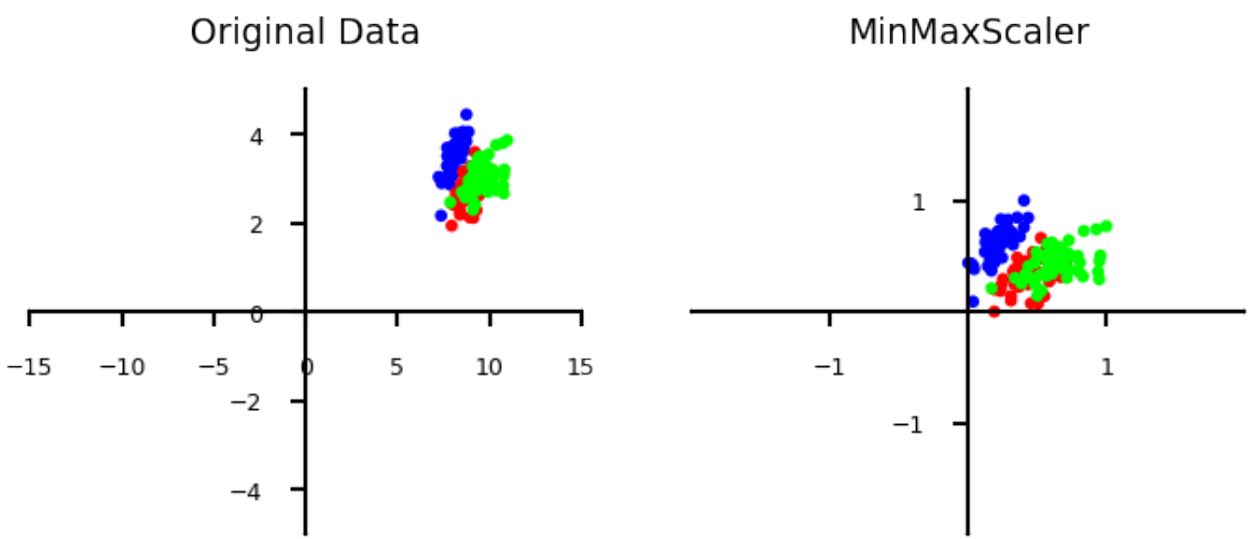
$$\mathbf{x_{new}} = \frac{\mathbf{x} - \mu}{\sigma}$$



Min-max scaling

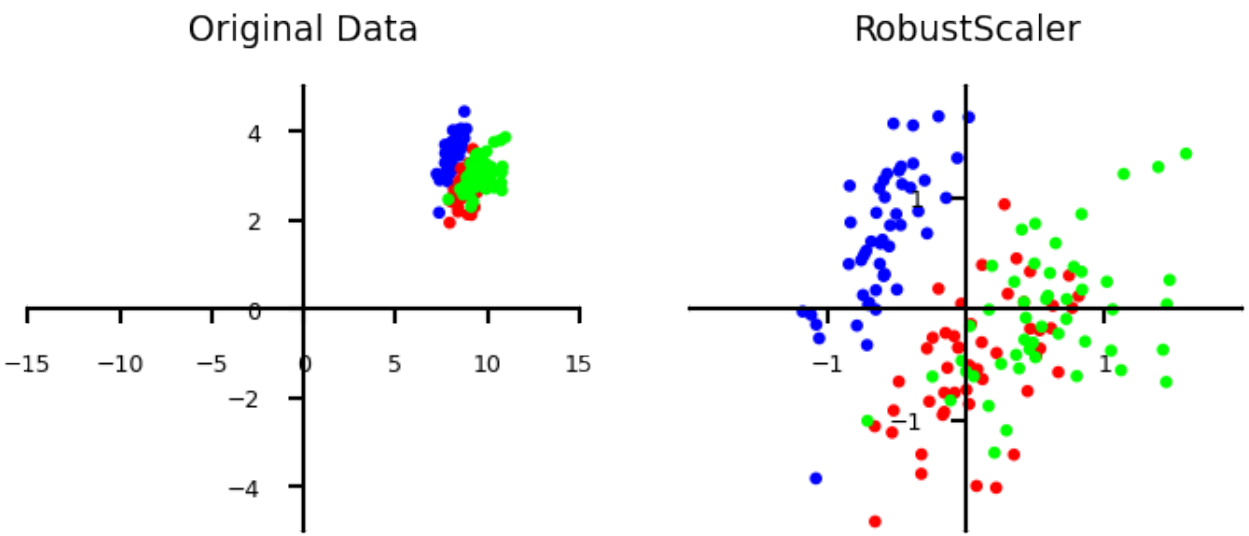
- Scales all features between a given *min* and *max* value (e.g. 0 and 1)
- Makes sense if min/max values have meaning in your data
- Sensitive to outliers

$$\mathbf{x_{new}} = \frac{\mathbf{x} - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \cdot (max - min) + min$$



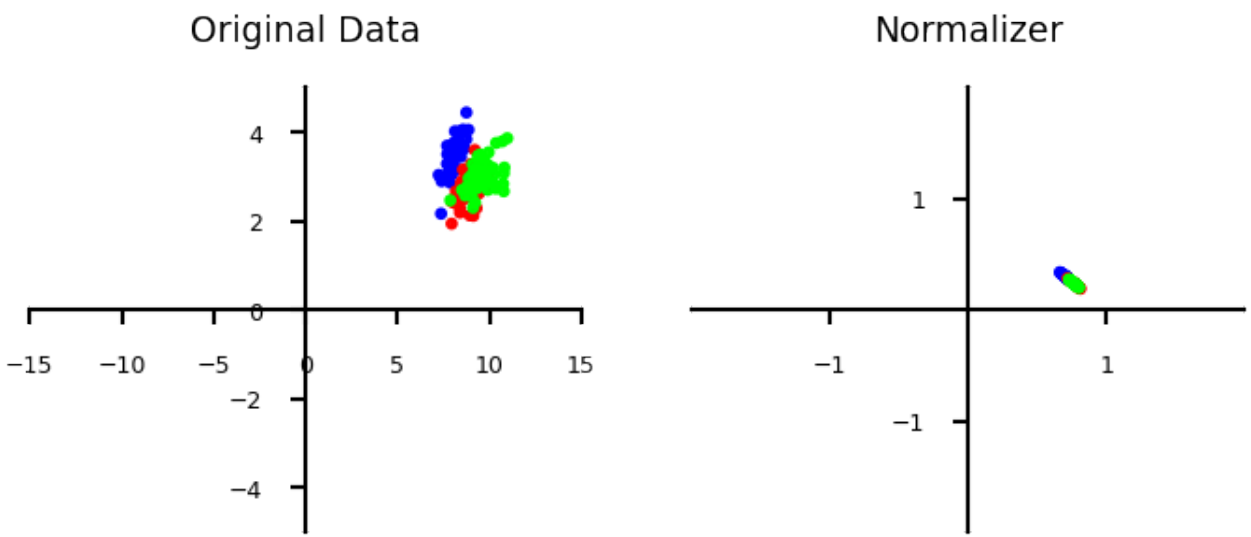
Robust scaling

- Subtracts the median, scales between quantiles q_{25} and q_{75}
- New feature has median 0, $q_{25} = -1$ and $q_{75} = 1$
- Similar to standard scaler, but ignores outliers



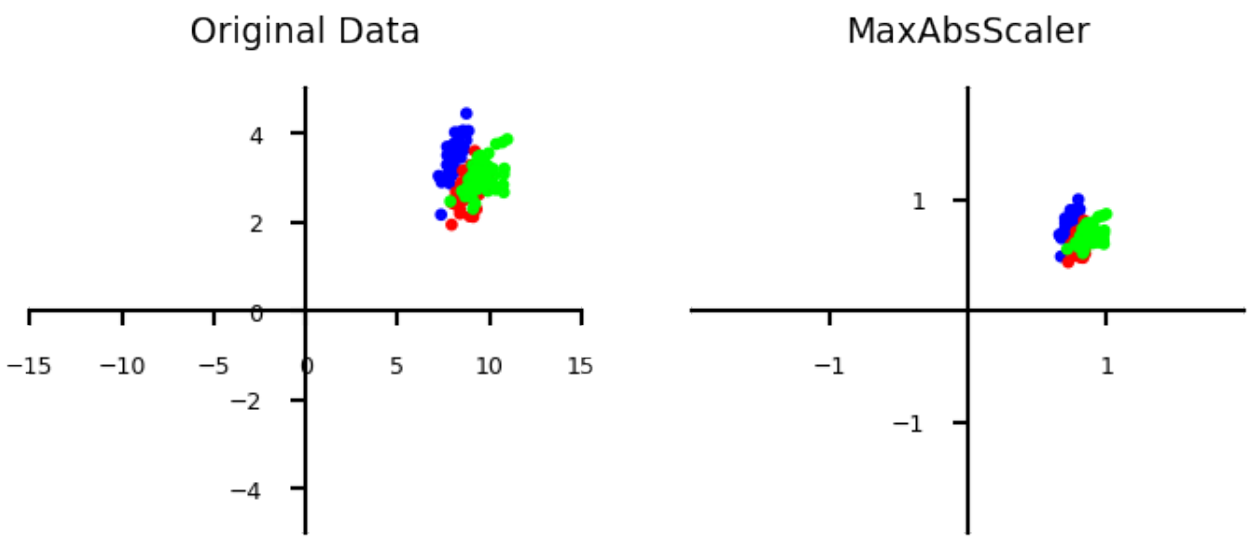
Normalization

- Makes sure that feature values of each point (each row) sum up to 1 (L1 norm)
  - Useful for count data (e.g. word counts in documents)
- Can also be used with L2 norm (sum of squares is 1)
  - Useful when computing distances in high dimensions
  - Normalized Euclidean distance is equivalent to cosine similarity



Maximum Absolute scaler

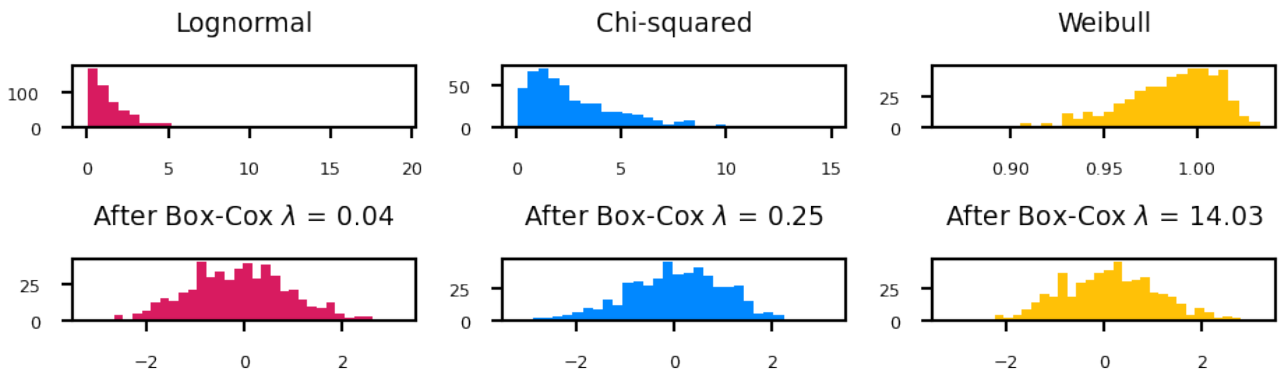
- For sparse data (many features, but few are non-zero)
  - Maintain sparseness (efficient storage)
- Scales all values so that maximum absolute value is 1
- Similar to Min-Max scaling without changing 0 values



Power transformations

- Some features follow certain distributions
  - E.g. number of twitter followers is log-normal distributed
- Box-Cox transformations transform these to normal distributions (λ is fitted)
  - Only works for positive values, use Yeo-Johnson otherwise

$$bc_\lambda(x) = \begin{cases} \log(x) & \lambda = 0 \\ \frac{x^\lambda - 1}{\lambda} & \lambda \neq 0 \end{cases}$$



Categorical feature encoding

- Many algorithms can only handle numeric features, so we need to encode the categorical ones

	boro	salary	vegan
0	Manhattan	103	0
1	Queens	89	0
2	Manhattan	142	0
3	Brooklyn	54	1
4	Brooklyn	63	1
5	Bronx	219	0

Ordinal encoding

- Simply assigns an integer value to each category in the order they are encountered
- Only really useful if there exist a natural order in categories
  - Model will consider one category to be 'higher' or 'closer' to another

	boro	boro_ordinal	salary
0	Manhattan	2	103
1	Queens	3	89
2	Manhattan	2	142
3	Brooklyn	1	54
4	Brooklyn	1	63
5	Bronx	0	219

One-hot encoding (dummy encoding)

- Simply adds a new 0/1 feature for every category, having 1 (hot) if the sample has that category
- Can explode if a feature has lots of values, causing issues with high dimensionality
- What if test set contains a new category not seen in training data?
  - Either ignore it (just use all 0's in row), or handle manually (e.g. resample)

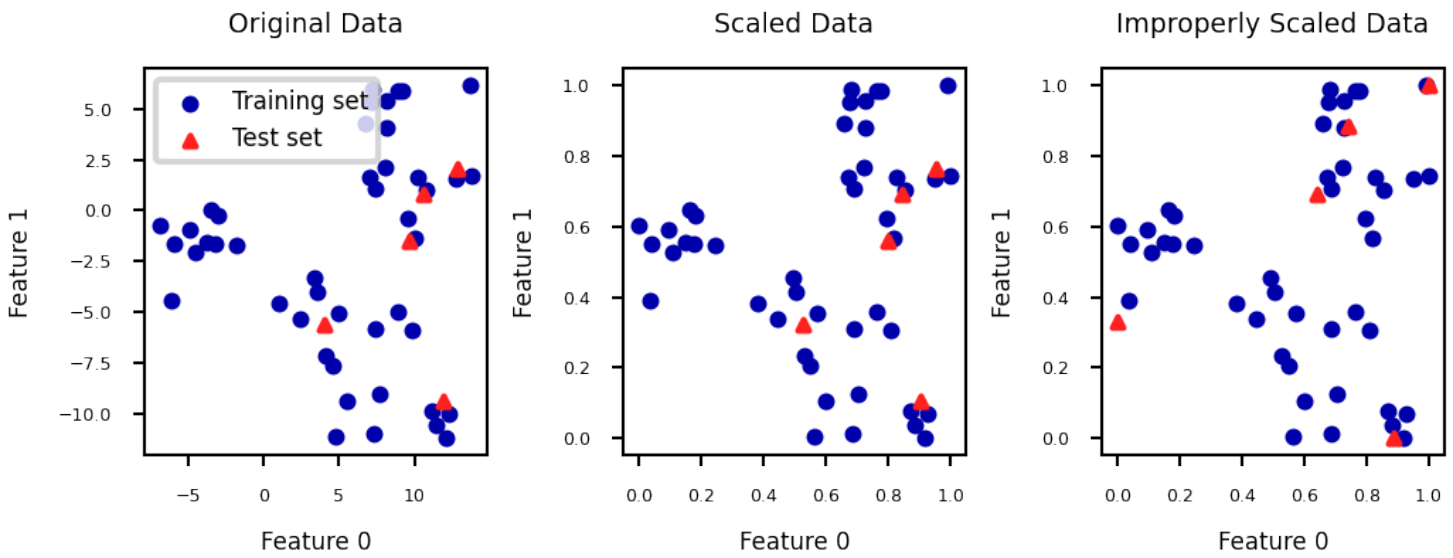
	boro	boro_Bronx	boro_Brooklyn	boro_Manhattan	boro_Queens	salary
0	Manhattan	0	0	1	0	103
1	Queens	0	0	0	1	89
2	Manhattan	0	0	1	0	142
3	Brooklyn	0	1	0	0	54
4	Brooklyn	0	1	0	0	63
5	Bronx	1	0	0	0	219

Applying data transformations

- Data transformations should always follow a fit-predict paradigm
  - Fit the transformer on the training data only
    - E.g. for a standard scaler: record the mean and standard deviation
  - Transform (e.g. scale) the training data, then train the learning model
  - Transform (e.g. scale) the test data, then evaluate the model
- Only scale the input features (X), not the targets (y)
- If you fit and transform the whole dataset before splitting, you get data leakage
  - You have looked at the test data before training the model
  - Model evaluations will be misleading
- If you fit and transform the training and test data separately, you distort the data
  - E.g. training and test points are scaled differently

Test set distortion

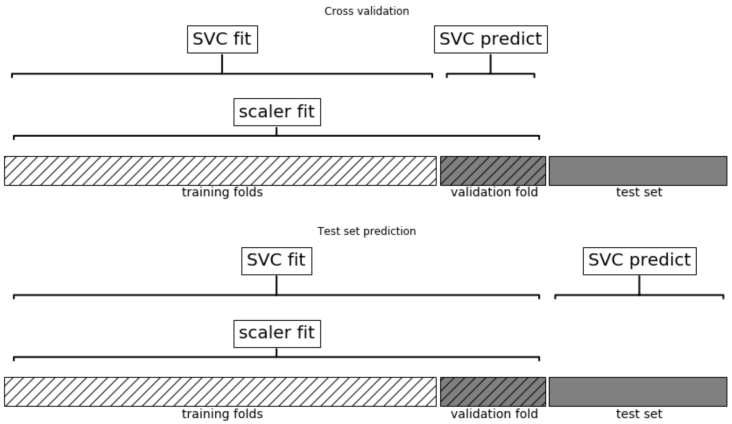
- Properly scaled: `fit` on training set, `transform` on training and test set
- Improperly scaled: `fit` and `transform` on the training and test data separately
  - Test data points nowhere near same training data points



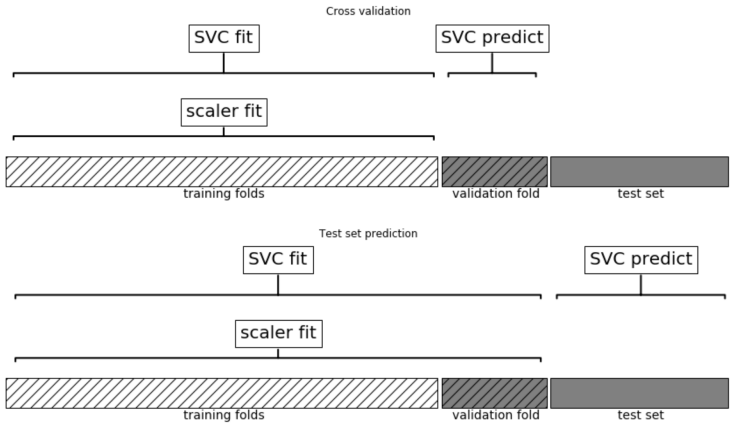
Data leakage

- Cross-validation: training set is split into training and validation sets for model selection
- Incorrect: Scaler is fit on whole training set before doing cross-validation
  - Data leaks from validation folds into training folds, selected model may be optimistic
- Right: Scaler is fit on training folds only

Information Leak



No Information leakage

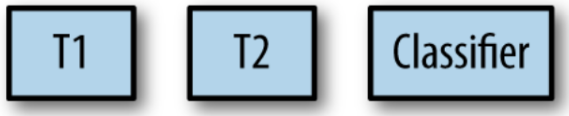


Pipelines

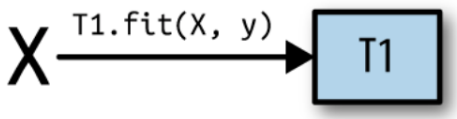
- A pipeline is a combination of data transformation and learning algorithms
- It has a `fit`, `predict`, and `score` method, just like any other learning algorithm
    - Ensures that data transformations are applied correctly

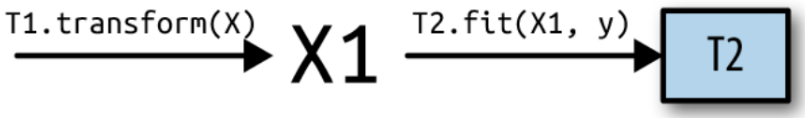
Pipelines (cont.)

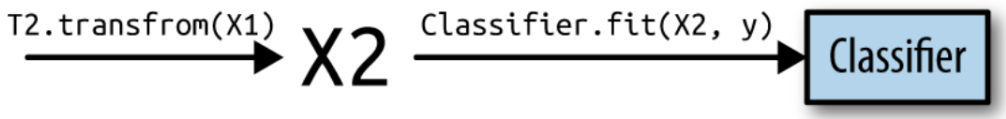

```
pipe = make_pipeline(T1(), T2(), Classifier())
```



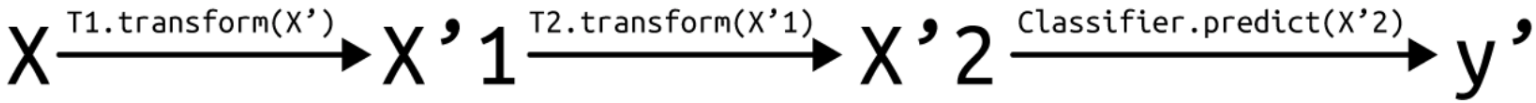

```
pipe.fit(X, y)
```








```
pipe.predict(X')
```



In practice (scikit-learn)

- A `pipeline` combines multiple processing *steps* in a single estimator
- All but the last step should be data transformer (have a `transform` method)

```
# Make pipeline, step names will be 'minmaxscaler' and 'linearsvc'
pipe = make_pipeline(MinMaxScaler(), LinearSVC())

# Build pipeline with named steps
pipe = Pipeline([("scaler", MinMaxScaler()), ("svm", LinearSVC())])

# Correct fit and score
score = pipe.fit(X_train, y_train).score(X_test, y_test)

# Retrieve trained model by name
svm = pipe.named_steps["svm"]

# Correct cross-validation
scores = cross_val_score(pipe, X, y)
```

ColumnTransformer and FeatureUnion

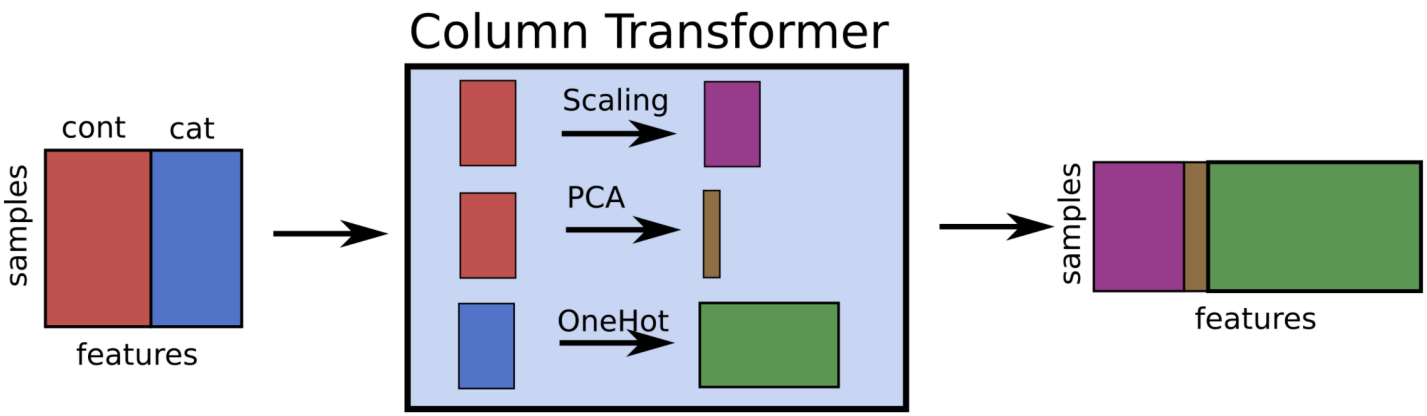
- If you want to apply different preprocessors to different columns, use `ColumnTransformer`
- If you want to merge pipelines, you can use `FeatureUnion` to concatenate columns

```
# 2 sub-pipelines, one for numeric features, other for categorical ones
numeric_pipe = make_pipeline(SimpleImputer(), StandardScaler())
categorical_pipe = make_pipeline(SimpleImputer(), OneHotEncoder())

# Using categorical pipe for features A,B,C, numeric pipe otherwise
preprocessor = make_column_transformer((categorical_pipe,
                                        ["A", "B", "C"]),
                                       remainder=numeric_pipe)

# Combine with learning algorithm in another pipeline
pipe = make_pipeline(preprocessor, LinearSVC())


# Feature union of PCA features and selected features
union = FeatureUnion([("pca", PCA()), ("selected", SelectKBest())])
pipe = make_pipeline(union, LinearSVC())
```

ColumnTransformer

- `ColumnTransformer` concatenates features in order

```
pipe = make_column_transformer((StandardScaler(), numeric_features),
                               (PCA(), numeric_features),
                               (OneHotEncoder(), categorical_features))
```



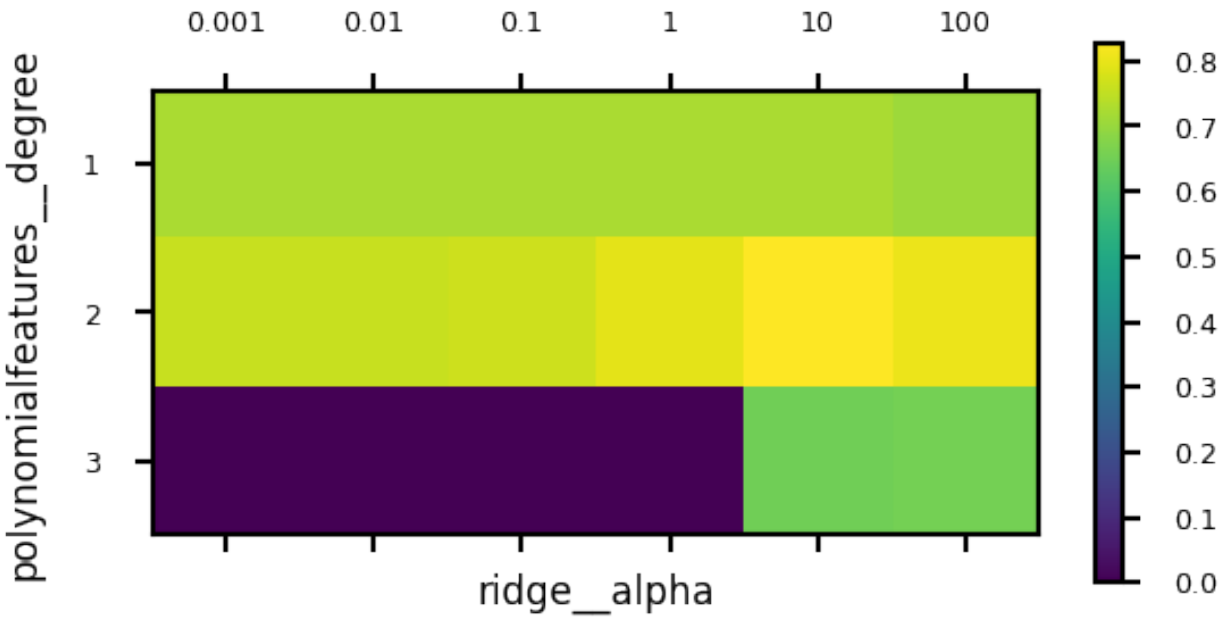
Pipeline selection

- We can safely use pipelines in model selection (e.g. grid search)
- Use `__` to refer to the hyperparameters of a step, e.g. `svm__C`

```
# Correct grid search (can have hyperparameters of any step)
param_grid = {'svm__C': [0.001, 0.01],
              'svm__gamma': [0.001, 0.01, 0.1, 1, 10, 100]}
grid = GridSearchCV(pipe, param_grid=param_grid).fit(X, y)

# Best estimator is now the best pipeline
best_pipe = grid.best_estimator_


# Tune pipeline and evaluate on held-out test set
grid = GridSearchCV(pipe, param_grid=param_grid).fit(X_train, y_train)
grid.score(X_test, y_test)
```

Example: Tune multiple steps at once

```
pipe = make_pipeline(StandardScaler(), PolynomialFeatures(), Ridge())
param_grid = {'polynomialfeatures__degree': [1, 2, 3],
              'ridge__alpha': [0.001, 0.01, 0.1, 1, 10, 100]}
grid = GridSearchCV(pipe, param_grid=param_grid).fit(X_train, y_train)
```



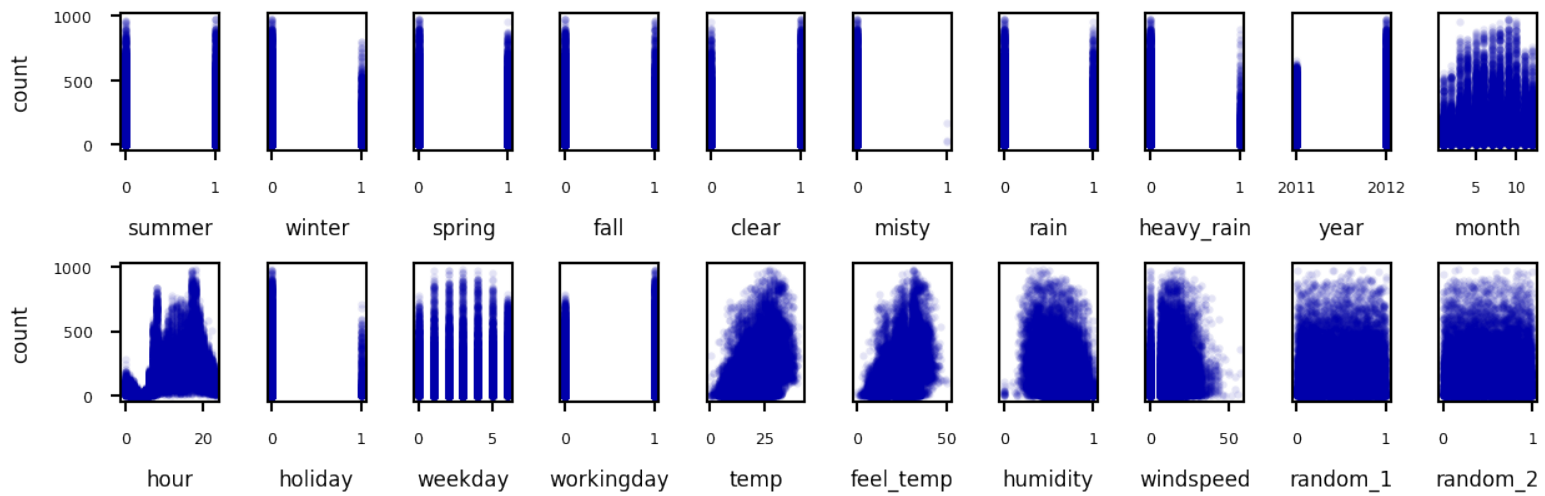
Automatic Feature Selection

It can be a good idea to reduce the number of features to only the most useful ones

- Simpler models that generalize better (less overfitting)
  - Curse of dimensionality (e.g. kNN)
  - Even models such as RandomForest can benefit from this
  - Sometimes it is one of the main methods to improve models (e.g. gene expression data)
- Faster prediction and training
  - Training time can be quadratic (or cubic) in number of features
- Easier data collection, smaller models (less storage)
- More interpretable models: fewer features to look at

Example: bike sharing

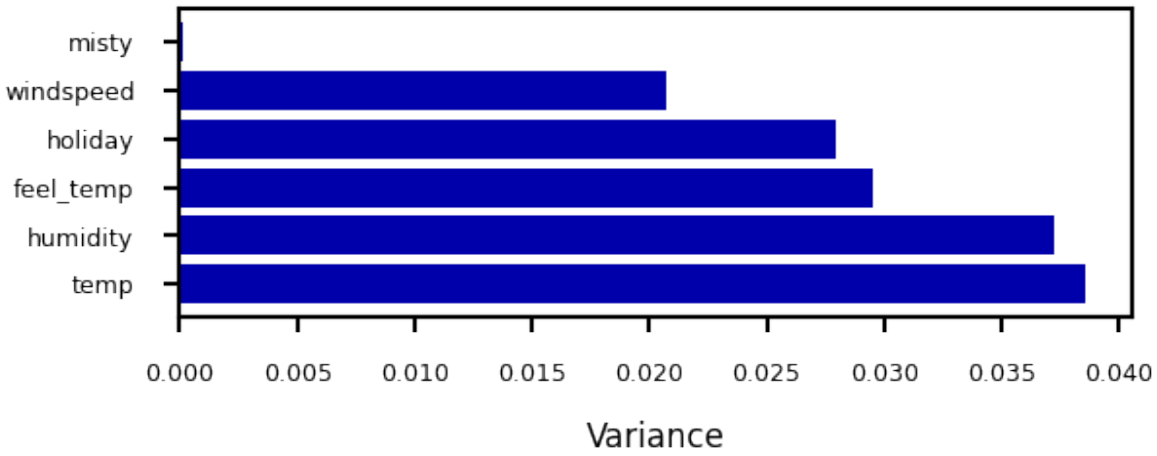
- The Bike Sharing Demand dataset shows the amount of bikes rented in Washington DC
- Some features are clearly more informative than others (e.g. temp, hour)
- Some are correlated (e.g. temp and feel_temp)
- We add two random features at the end



Unsupervised feature selection

- Variance-based
  - Remove (near) constant features
    - Choose a small variance threshold
  - Scale features before computing variance!
  - Infrequent values may still be important
- Covariance-based
  - Remove correlated features
  - The small differences may actually be important
    - You don't know because you don't consider the target

Unsupervised feature selection (cont.)



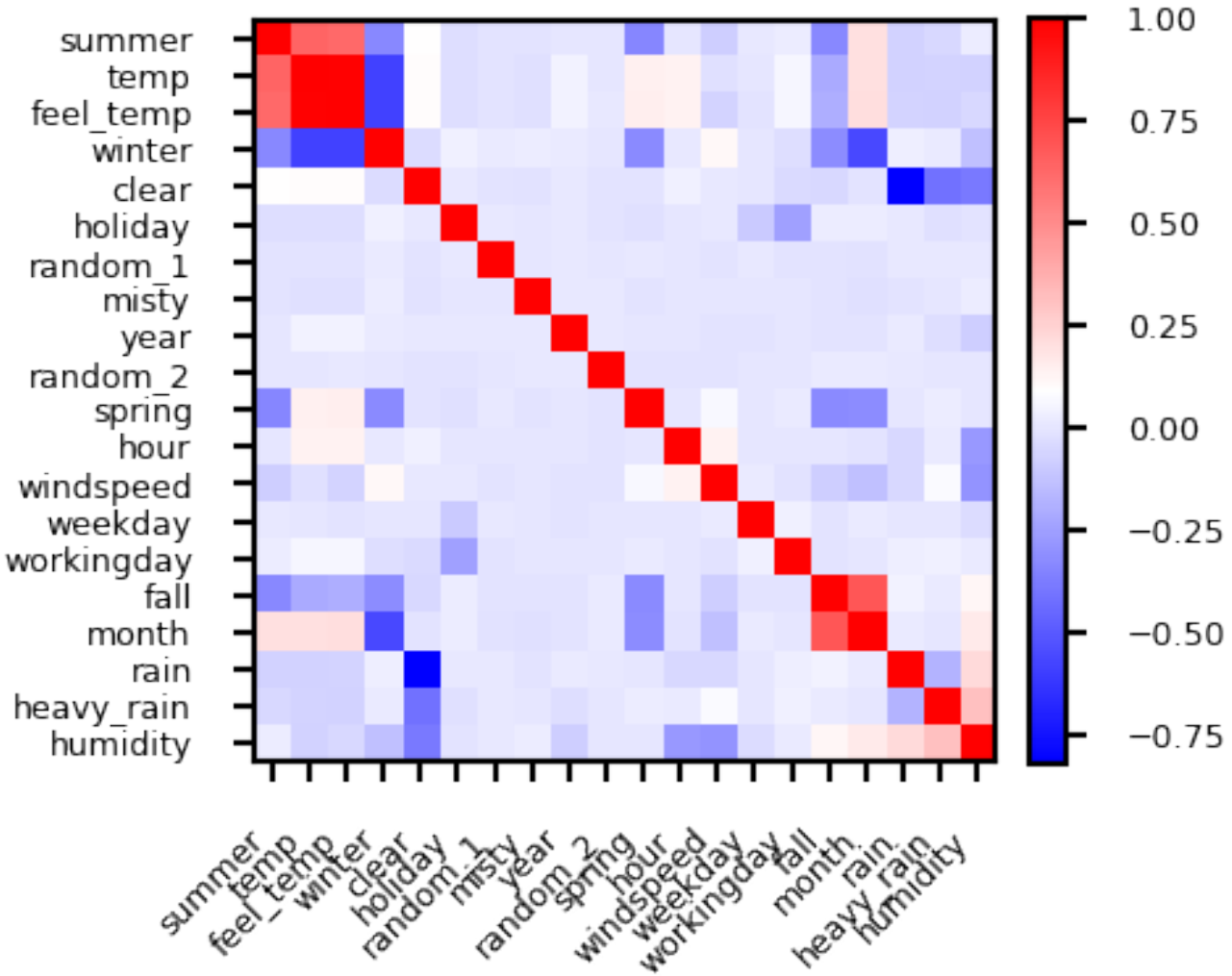
Covariance based feature selection

- Remove features X_i $(= \mathbf{X}_{\cdot,i})$ that are highly correlated (have high correlation coefficient ρ)

$$\rho(X_1, X_2) = \frac{\text{cov}(X_1, X_2)}{\sigma(X_1)\sigma(X_2)} = \frac{\frac{1}{N-1}\sum_i (X_{i,1} - \overline{X_1})(X_{i,2} - \overline{X_2})}{\sigma(X_1)\sigma(X_2)}$$

- Should we remove `feel_temp`? Or `temp`? Maybe one correlates more with the target?

Covariance based feature selection (cont.)



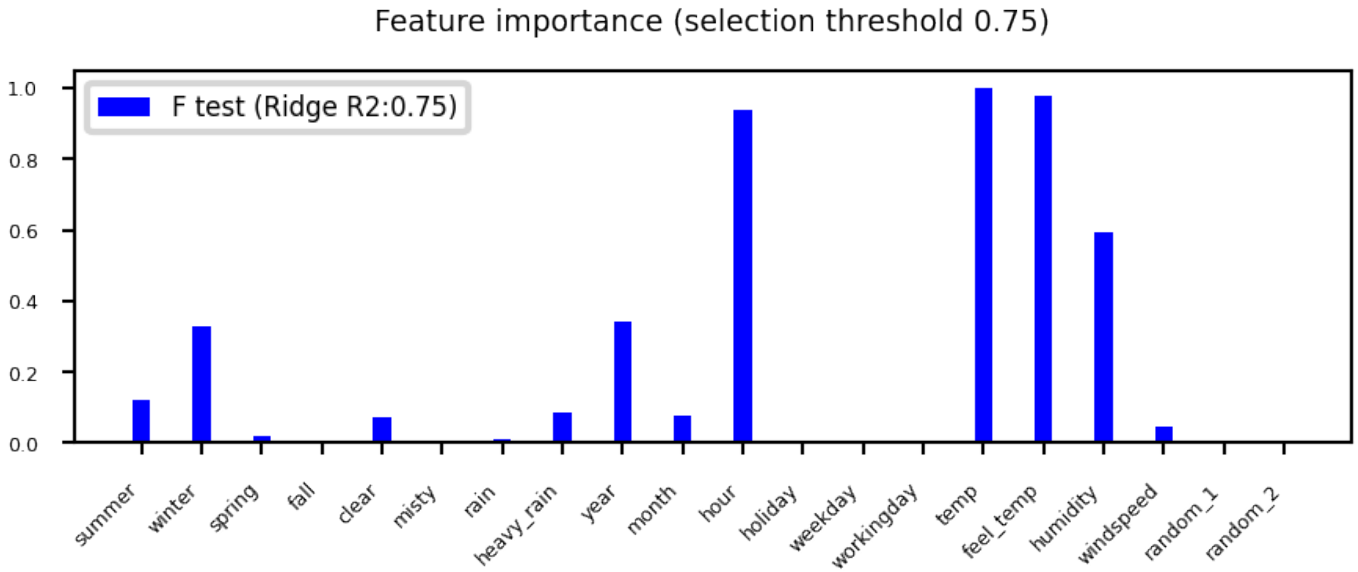
Supervised feature selection: overview

- Univariate: F-test and Mutual Information
- Model-based: Random Forests, Linear models, kNN
- Wrapping techniques (black-box search)
- Permutation importance

Univariate statistics (F-test)

- Consider each feature individually (univariate), independent of the model that you aim to apply
- Use a statistical test: is there a *linear statistically significant relationship* with the target?
- Use F-statistic (or corresponding p value) to rank all features, then select features using a threshold
  - Best k, best $k\%$, probability of removing useful features (FPR), ...
- Cannot detect correlations (e.g. temp and feel_temp) or interactions (e.g. binary features)

Univariate statistics (F-test) (cont.)



F-statistic

- For regression: does feature X_i correlate (positively or negatively) with the target y?

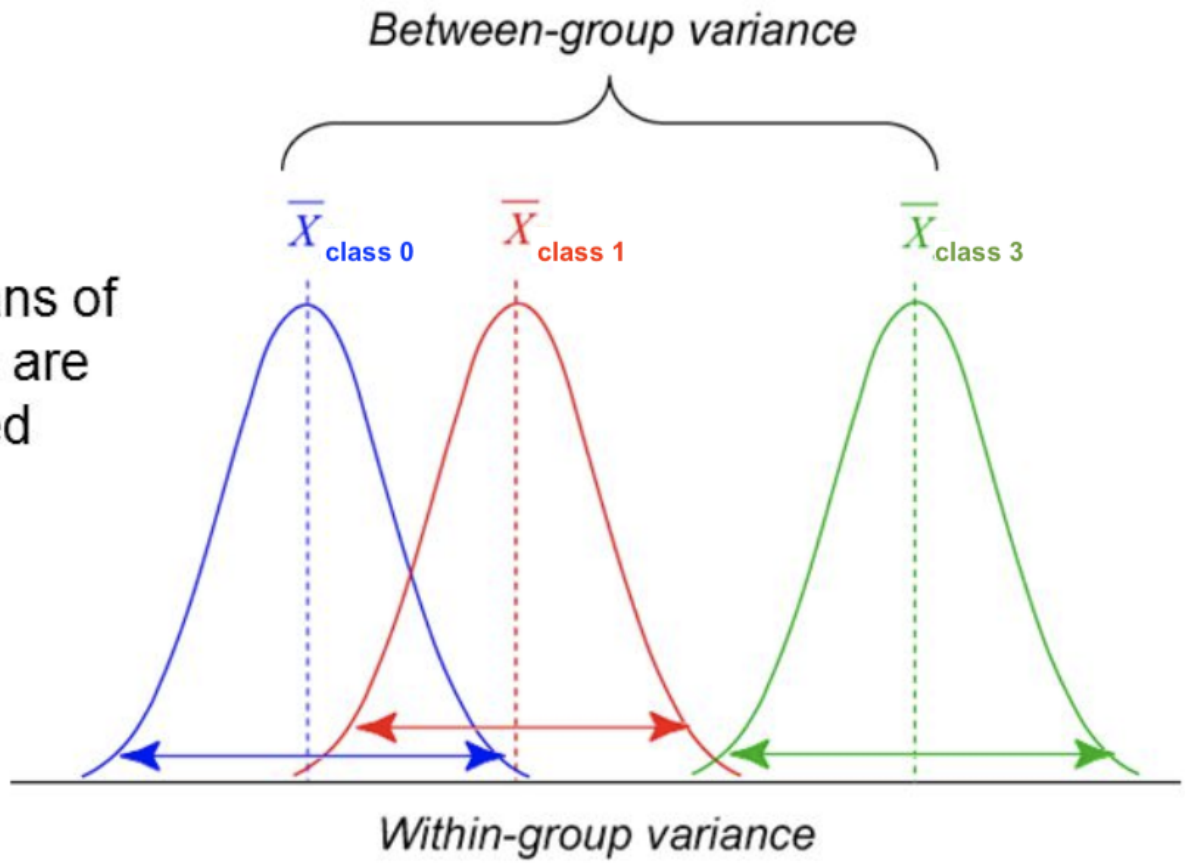
$$\text{F-statistic} = \frac{\rho(X_i, y)^2}{1 - \rho(X_i, y)^2} \cdot (N - 1)$$

- For classification: uses ANOVA: does X_i explain the between-class variance?
  - Alternatively, use the χ^2 test (only for categorical features)

$$\text{F-statistic} = \frac{\text{within-class variance}}{\text{between-class variance}} = \frac{\text{var}(\overline{X_i})}{\text{var}(X_i)}$$

F-statistic (cont.)

The means of 3 groups are compared



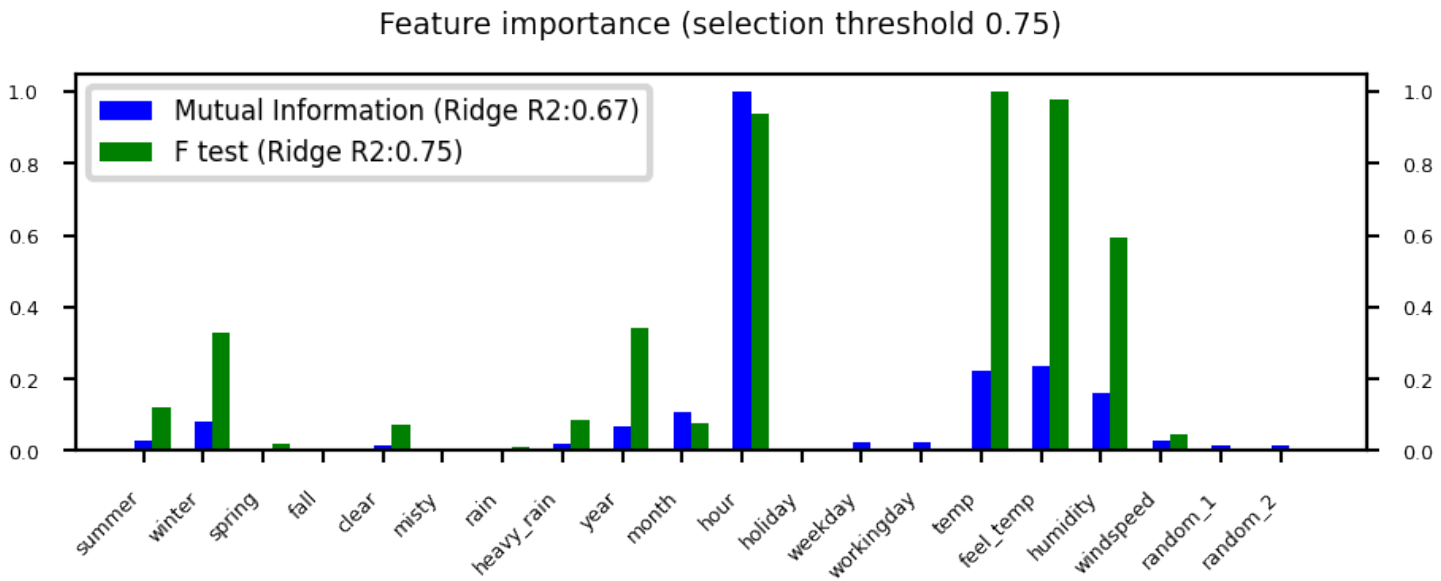
Mutual information

- Measures how much information X_i gives about the target Y. In terms of entropy H:

$$MI(X, Y) = H(X) + H(Y) - H(X, Y)$$

- Idea: estimate $H(X)$ as the average distance between a data point and its k Nearest Neighbors
  - You need to choose k and say which features are categorical
- Captures complex dependencies (e.g. hour, month), but requires more samples to be accurate

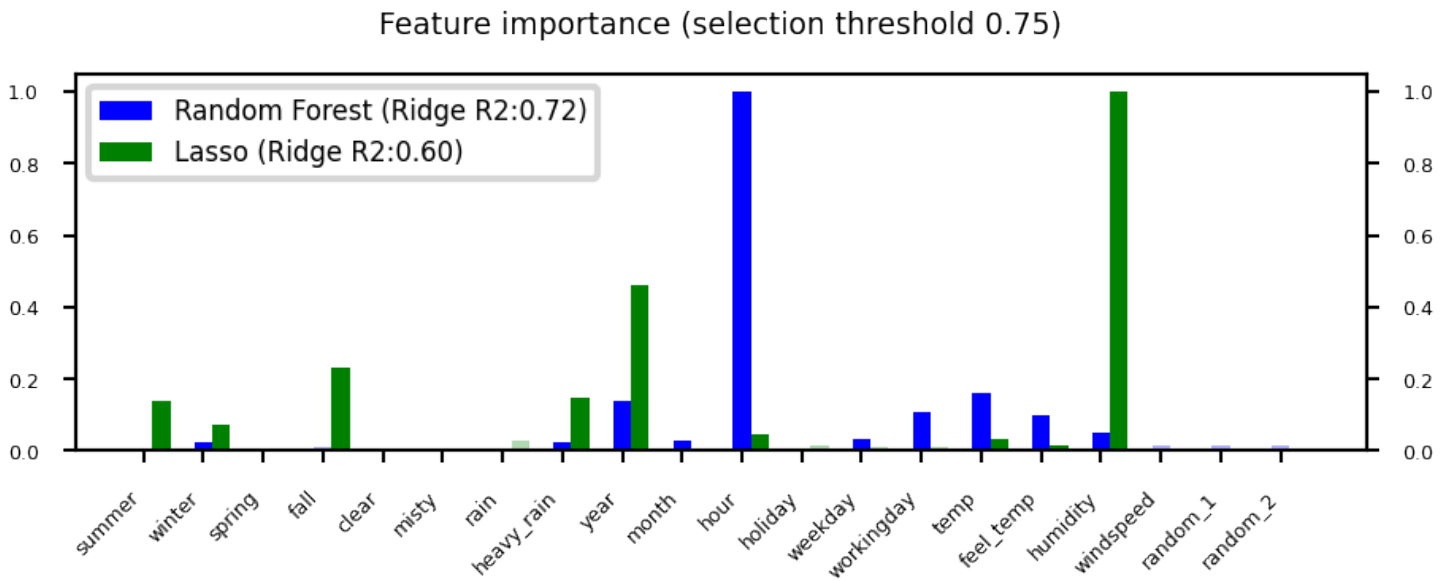
Mutual information (cont.)



Model-based Feature Selection

- Use a **tuned(!)** supervised model to judge the importance of each feature
  - Linear models (Ridge, Lasso, LinearSVM, ...): features with highest weights (coefficients)
  - Tree–based models: features used in first nodes (high information gain)
- Selection model can be different from the one you use for final modelling
- Captures interactions: features are more/less informative in combination (e.g. winter, temp)
- RandomForests: learns complex interactions (e.g. hour), but biased to high cardinality features

Model-based Feature Selection (cont.)



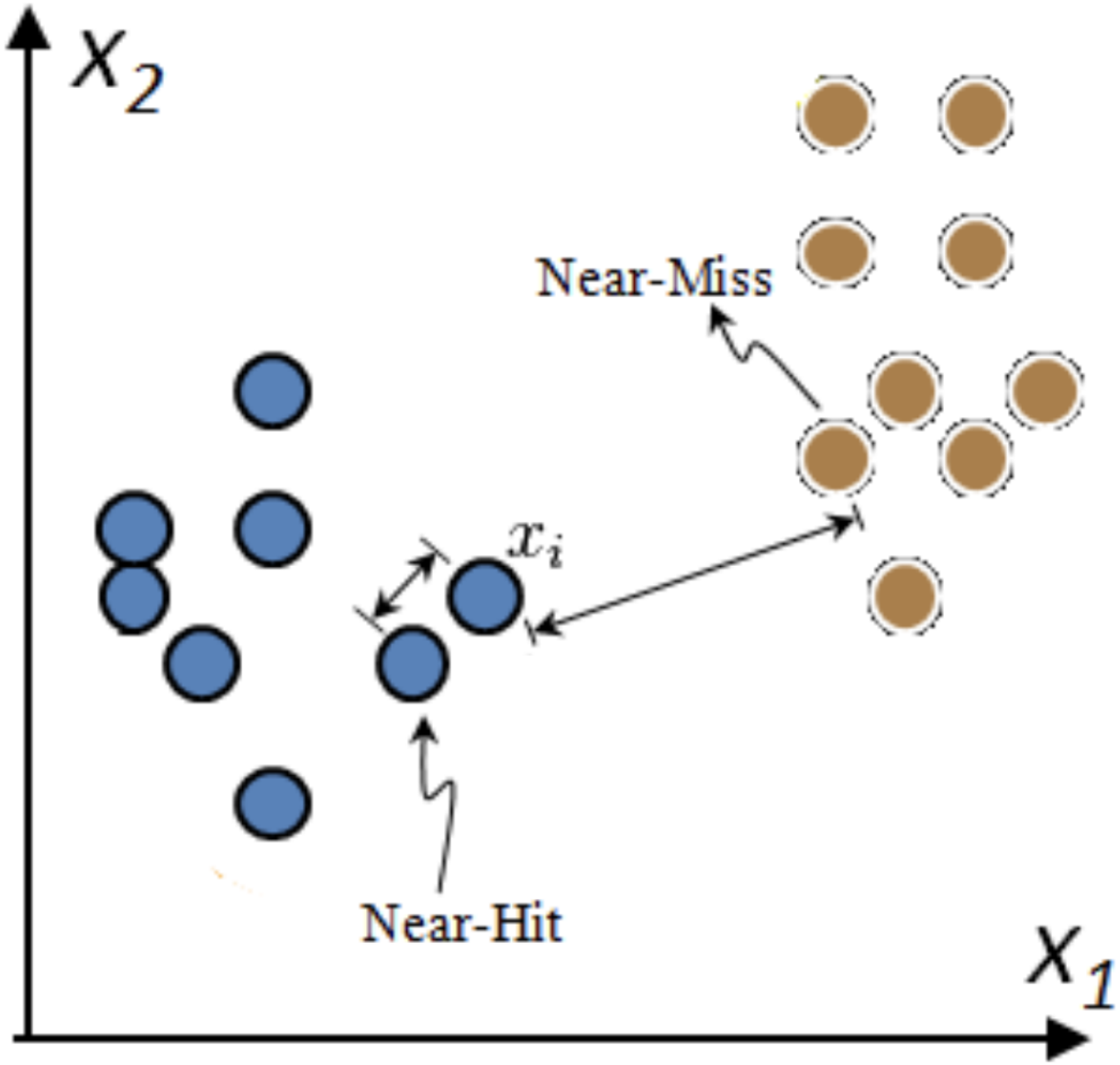
Relief: Model-based selection with kNN

- For l iterations, choose a random point $\mathbf{x}_i$ and find k nearest neighbors $\mathbf{x}_k$
- Increase feature weights if $\mathbf{x}_i$ and $\mathbf{x}_k$ have different class (near miss), else decrease

$$\mathbf{w}_i = \mathbf{w}_{i-1} + (\mathbf{x}_i - \text{nearMiss}_i)^2 - (\mathbf{x}_i - \text{nearHit}_i)^2$$

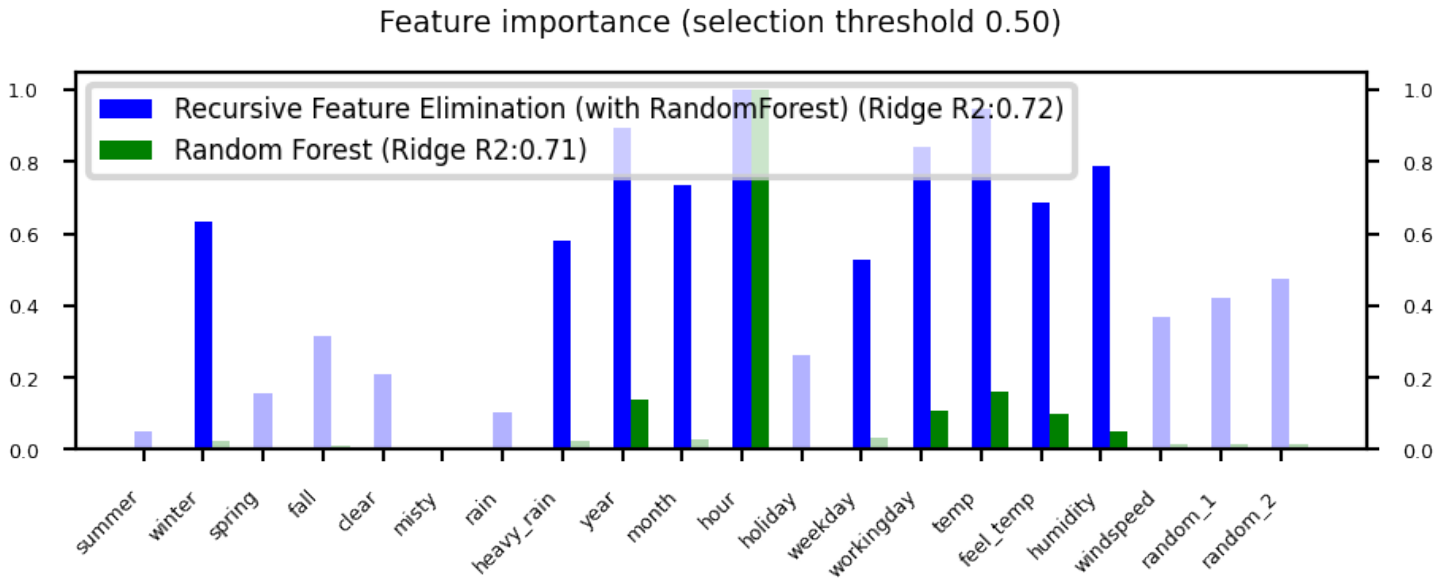
- Many variants: ReliefF (uses L1 norm, faster), RReliefF (for regression), ...

Relief: Model-based selection with kNN (cont.)



Iterative Model-based Feature Selection

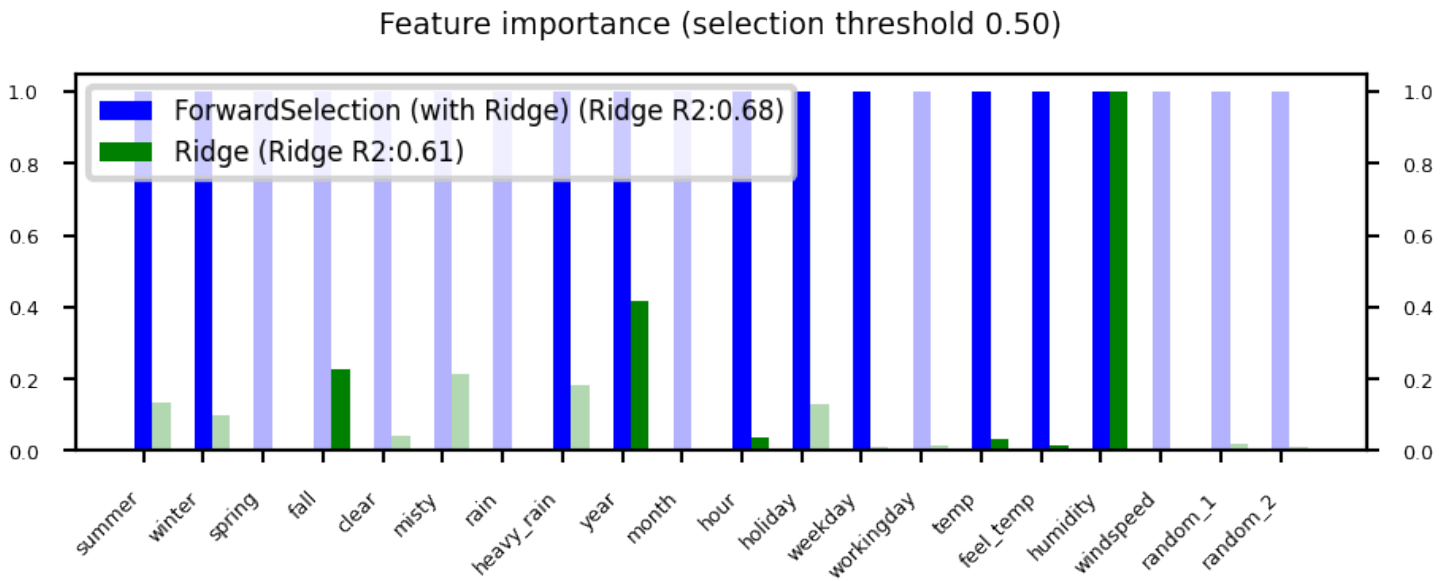
- Dropping many features at once is not ideal: feature importance may change in subset
- Recursive Feature Elimination (RFE)
  - Remove s least important feature(s), recompute remaining importances, repeat
- Can be rather slow



Sequential feature selection (Wrapping)

- Evaluate your model with different sets of features, find best subset based on performance
- Greedy black-box search (can end up in local minima)
  - Backward selection: remove least important feature, recompute importances, repeat
  - Forward selection: set aside most important feature, recompute importances, repeat
  - Floating: add best new feature, remove worst one, repeat (forward or backward)
- Stochastic search: use random mutations in candidate subset (e.g. simulated annealing)

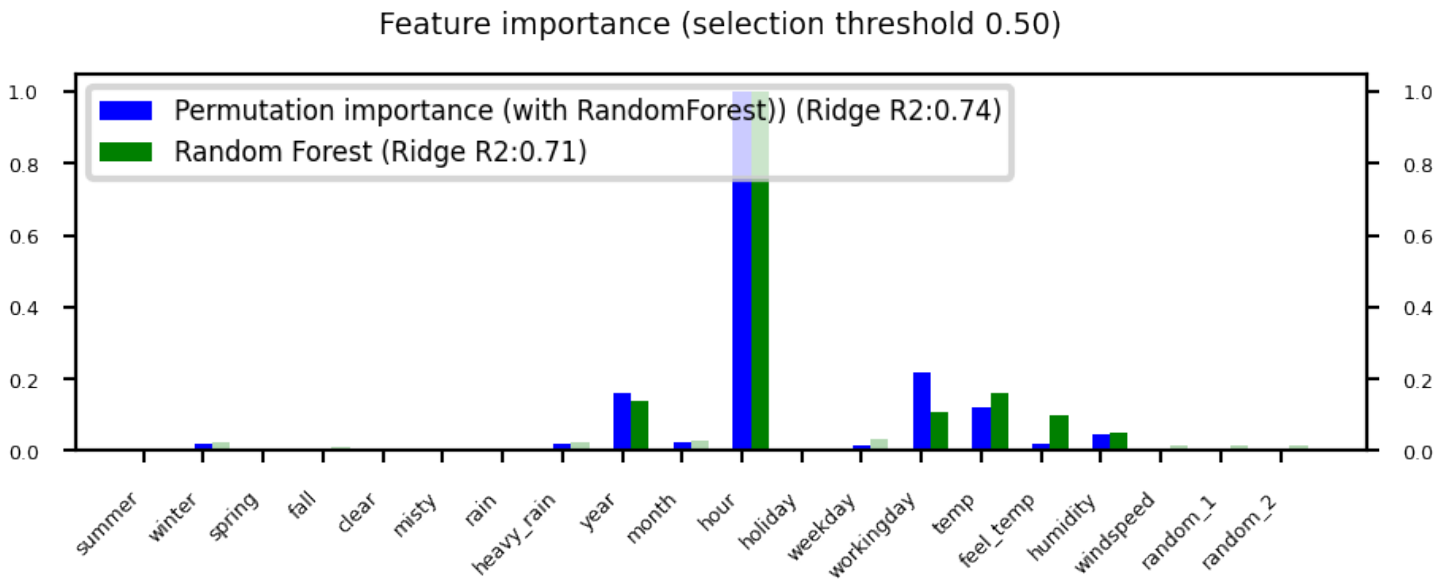
Sequential feature selection (Wrapping) (cont.)



Permutation feature importance

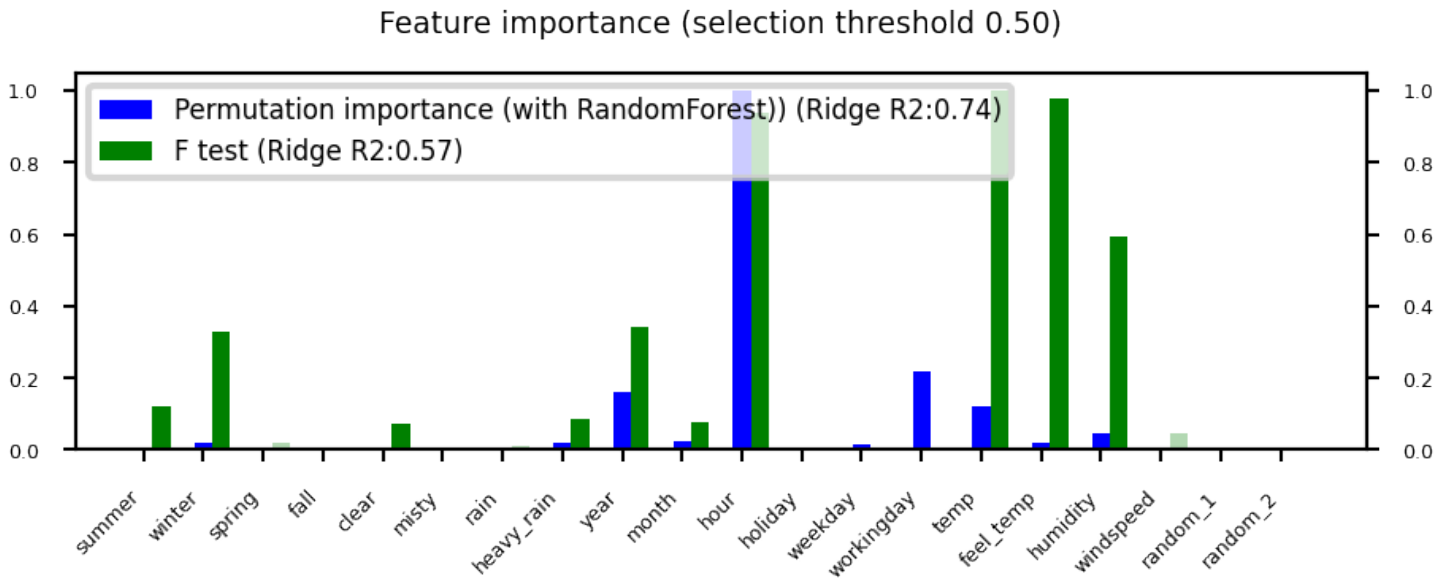
- Defined as the decrease in model performance when a single feature value is randomly shuffled
  - This breaks the relationship between the feature and the target
- Model agnostic, metric agnostic, and can be calculated many times with different permutations
- Can be applied to unseen data (not possible with model-based techniques)
- Less biased towards high-cardinality features (compared with RandomForests)

Permutation feature importance (cont.)



Comparison

- Feature importances (scaled) and cross-validated R^2 score of pipeline
  - Pipeline contains feature selection + Ridge
- Selection threshold value ranges from 25% to 100% of all features
- Best method ultimately depends on the problem and dataset at hand



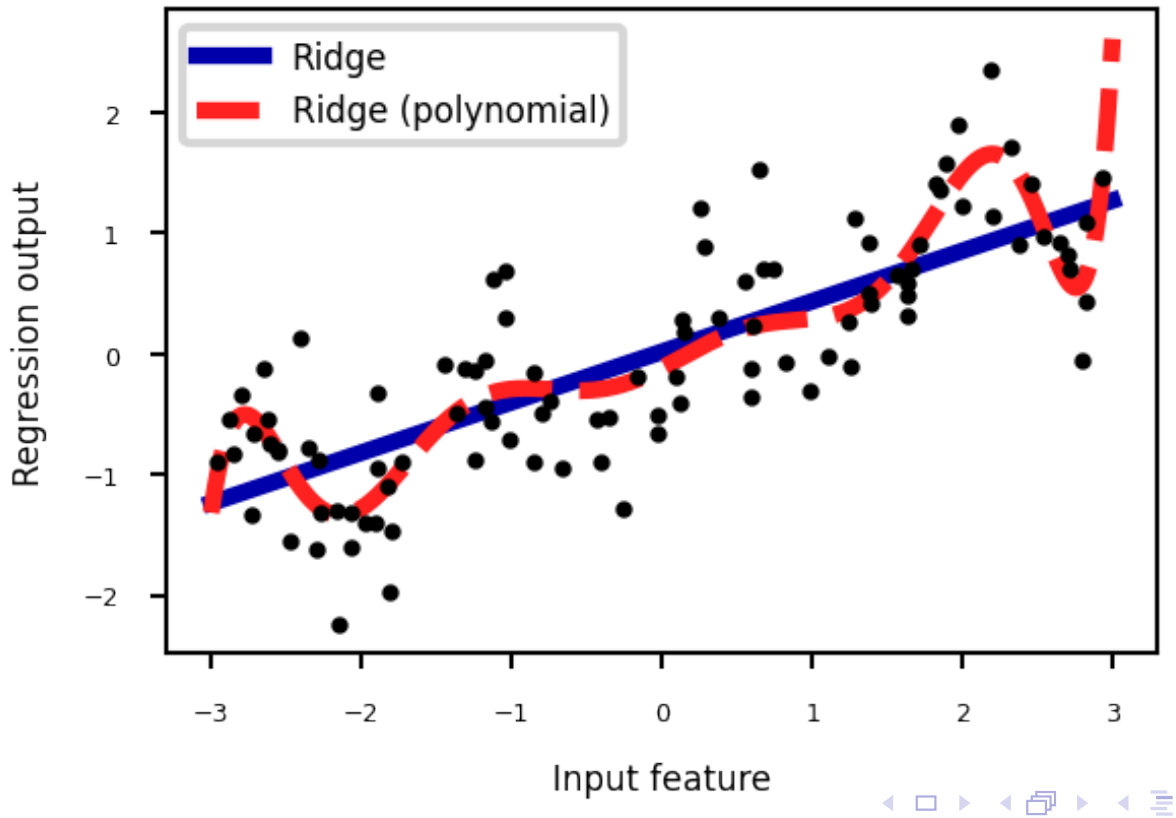
Feature Engineering

- Create new features based on existing ones
  - Polynomial features
  - Interaction features
  - Binning
- Mainly useful for simple models (e.g. linear models)
  - Other models can learn interactions themselves
  - But may be slower, less robust than linear models

Polynomials

- Add all polynomials up to degree d and all products
  - Equivalent to polynomial basis expansions

$$[1, x_1, \ldots, x_p] \rightarrow [1, x_1, \ldots, x_p, x_1^2, \ldots, x_p^2, \ldots, x_p^d, x_1 x_2, \ldots, x_{p-1} x_p]$$

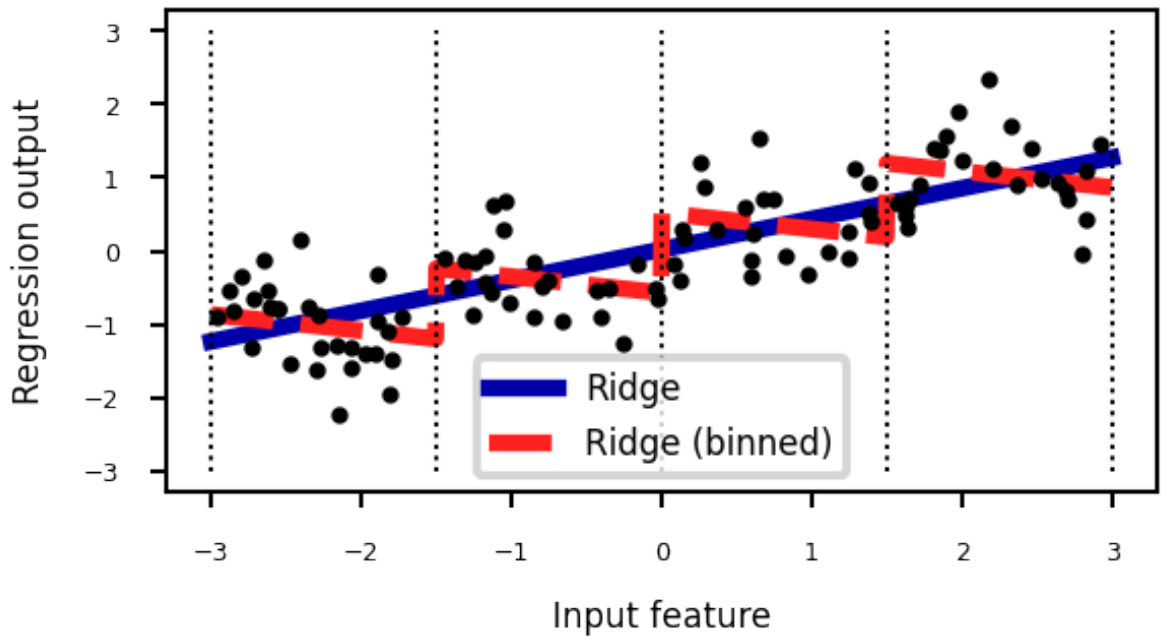


Binning

- Partition numeric feature values into n intervals (bins)
- Create n new one-hot features, 1 if original value falls in corresponding bin
- Models different intervals differently (e.g. different age groups)

orig	**[-3.0,-1.5]**	**[-1.5,0.0]**	**[0.0,1.5]**	**[1.5,3.0]**
-0.752759	0.000000	1.000000	0.000000	0.000000
2.704286	0.000000	0.000000	0.000000	1.000000
1.391964	0.000000	0.000000	1.000000	0.000000

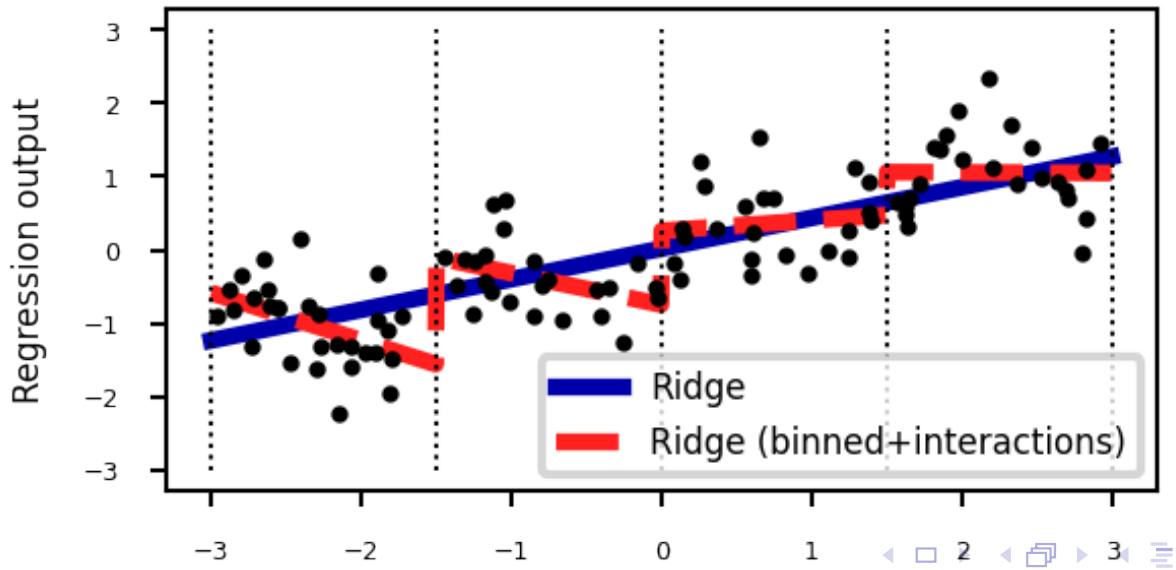
Binning (cont.)



Binning + interaction features

- Add *interaction features* (or *product features*)
  - Product of the bin encoding and the original feature value
  - Learn different weights per bin

orig	b0	b1	b2	b3	X*b0	X*b1	X*b2	X*b3
-0.752759	0.000000	1.000000	0.000000	0.000000	-0.752759	-0.000000	-0.000000	-0.000000
2.704286	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	2.704286
1.391964	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.391964	0.000000



Categorical feature interactions

- One-hot-encode categorical feature
- Multiply every one-hot-encoded column with every numeric feature
- Allows to built different submodels for different categories

	gender	age	pageviews	time
0	M	14	70	269
1	F	16	12	1522
2	M	12	42	235
3	F	25	64	63
4	F	22	93	21

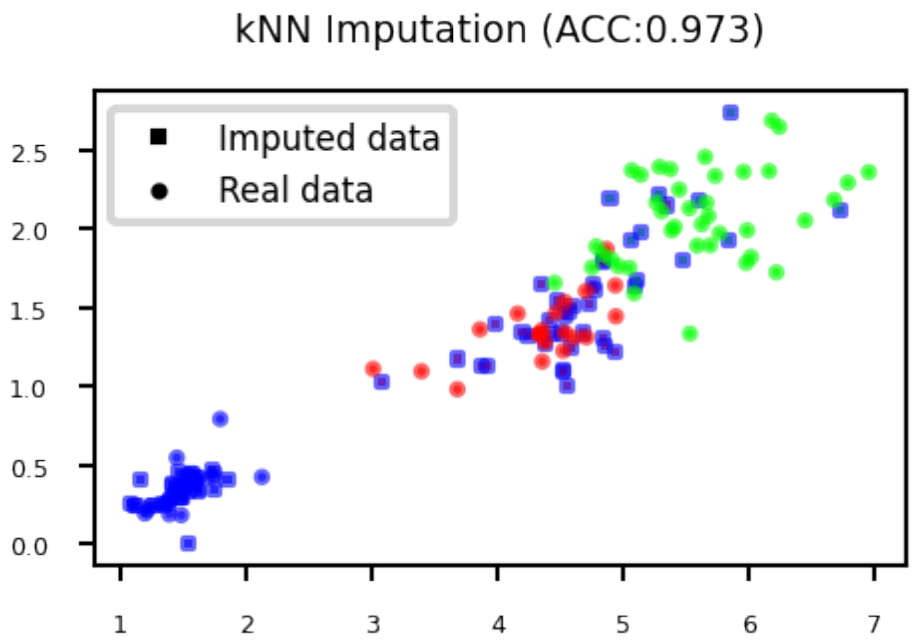
age_M	pageviews_M	time_M	gender_M_M	gender_F_M	age_F	pageviews_F	time_F	gender_F_F
14	70	269	1	0	0	0	0	0
0	0	0	0	0	16	12	1522	1
12	42	235	1	0	0	0	0	0
0	0	0	0	0	25	64	63	1
0	0	0	0	0	22	93	21	1

Missing value imputation

- Data can be missing in different ways:
  - Missing Completely at Random (MCAR): purely random points are missing
  - Missing at Random (MAR): something affects missingness, but no relation with the value
    - E.g. faulty sensors, some people don't fill out forms correctly
  - Missing Not At Random (MNAR): systematic missingness linked to the value
    - Has to be modelled or resolved (e.g. sensor decay, sick people leaving study)
- Missingness can be encoded in different ways: `'?'`, `'-1'`, `'unknown'`, `'NA'`,...
- Also labels can be missing (remove example or use semi-supervised learning)

Overview

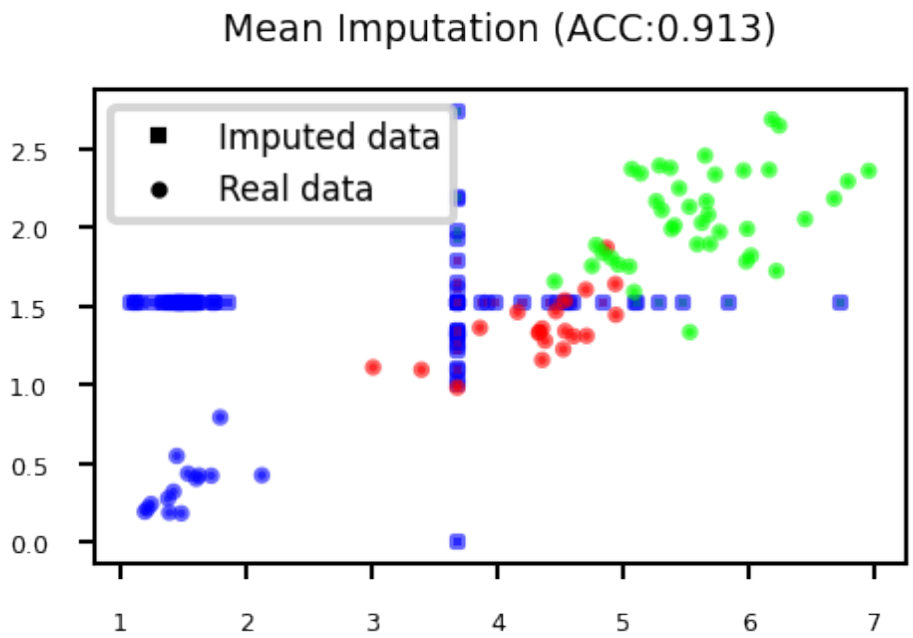
- Mean/constant imputation
- kNN-based imputation
- Iterative (model-based) imputation
- Matrix Factorization techniques



Mean imputation

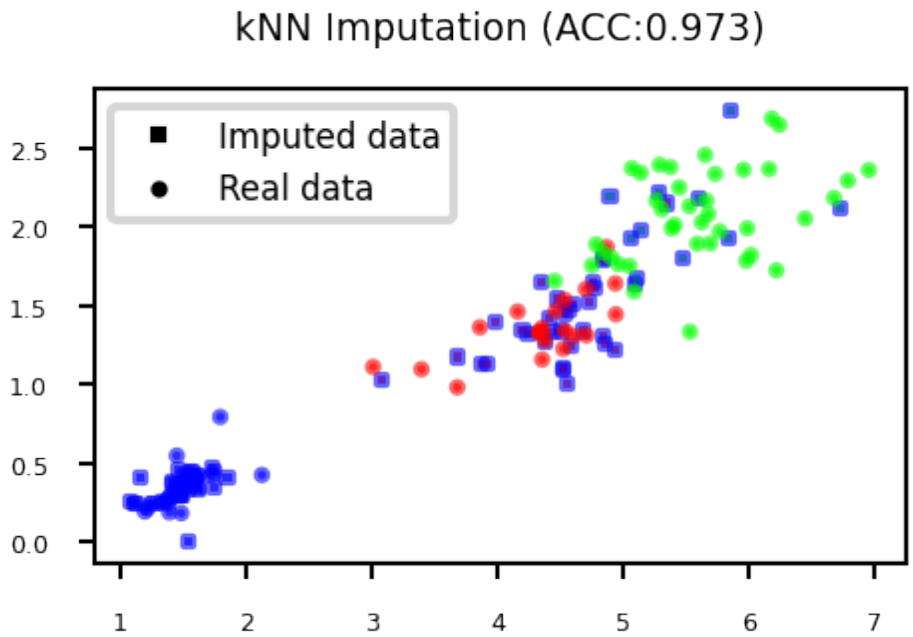
- Replace all missing values of a feature by the same value
  - Numerical features: mean or median
  - Categorical features: most frequent category
  - Constant value, e.g. 0 or `'missing'` for text features
- Optional: add an indicator column for missingness
- Example: Iris dataset (randomly removed values in 3rd and 4th column)

Mean imputation (cont.)



kNN imputation

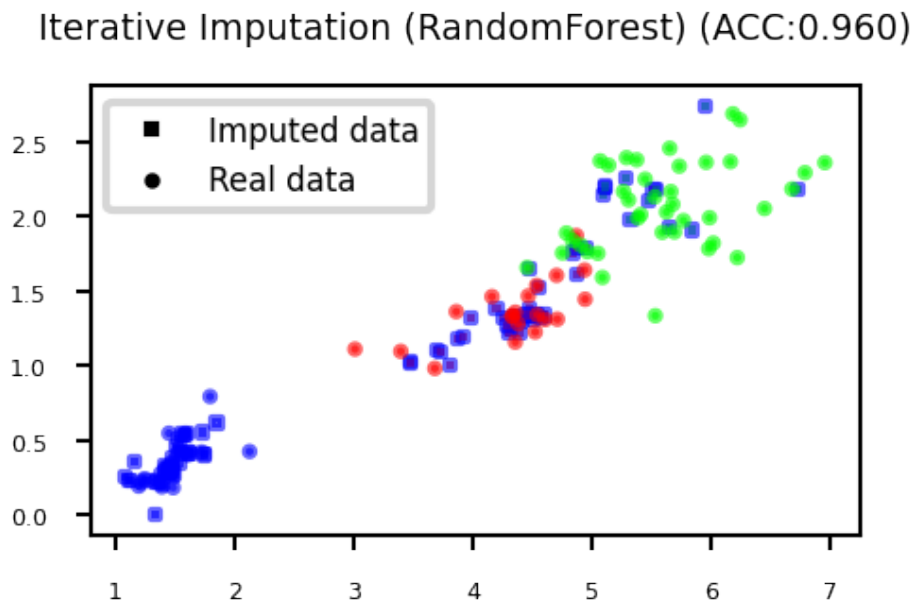
- Use special version of kNN to predict value of missing points
- Uses only non-missing data when computing distances



Iterative (model-based) Imputation

- Better known as Multiple Imputation by Chained Equations (MICE)
- Iterative approach
  - Do first imputation (e.g. mean imputation)
  - Train model (e.g. RandomForest) to predict missing values of a given feature
  - Train new model on imputed data to predict missing values of the next feature
    - Repeat m times in round-robin fashion, leave one feature out at a time

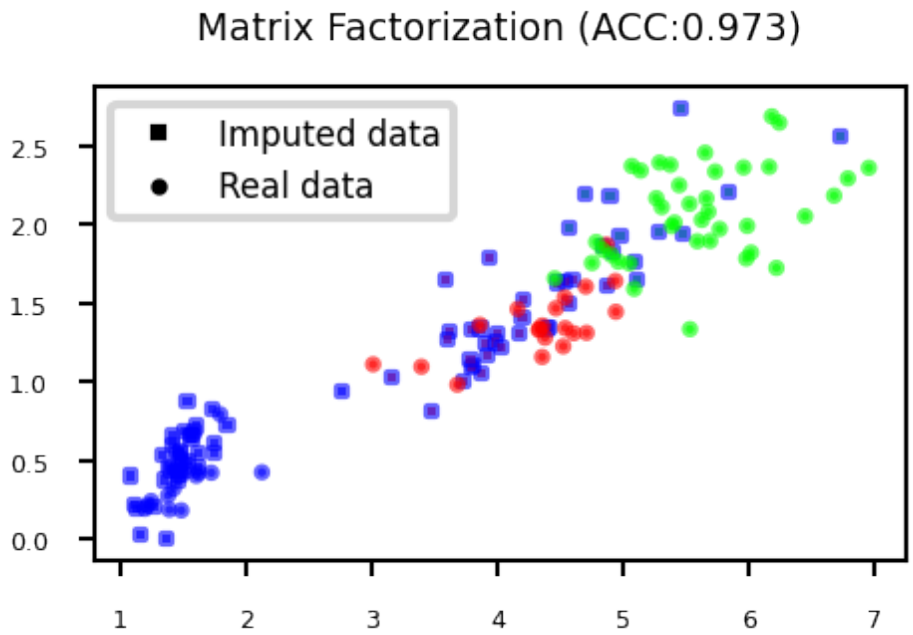
Iterative (model-based) Imputation (cont.)



Matrix Factorization

- Basic idea: low-rank approximation
  - Replace missing values by 0
  - Factorize $\mathbf{X}$ with rank r: $\mathbf{X}^{n \times p} = \mathbf{U}^{n \times r} \mathbf{V}^{r \times p}$
    - With n data points and p features
    - Solved using gradient descent
  - Recompute $\mathbf{X}$: now complete

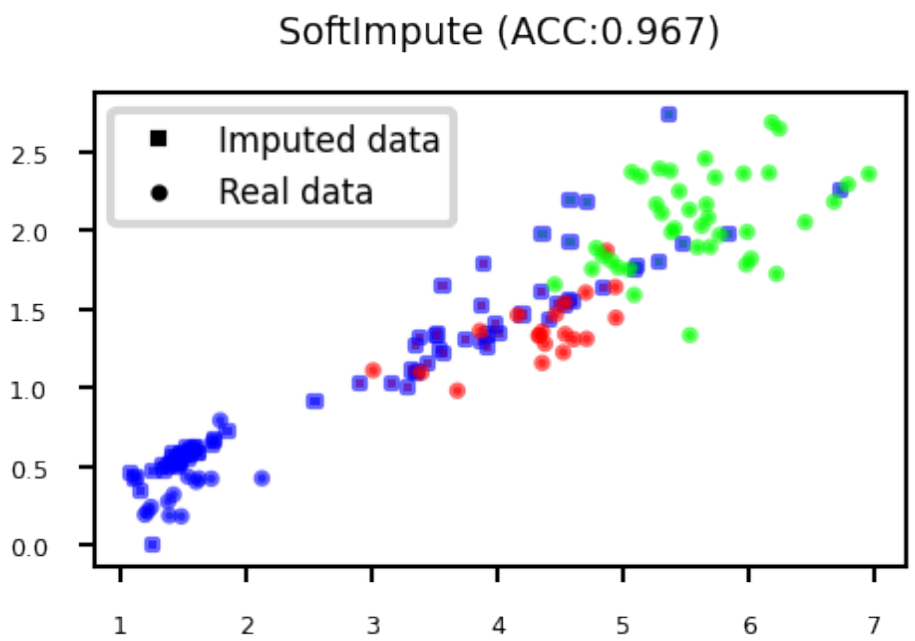
Matrix Factorization (cont.)



Soft-thresholded Singular Value Decomposition (SVD)

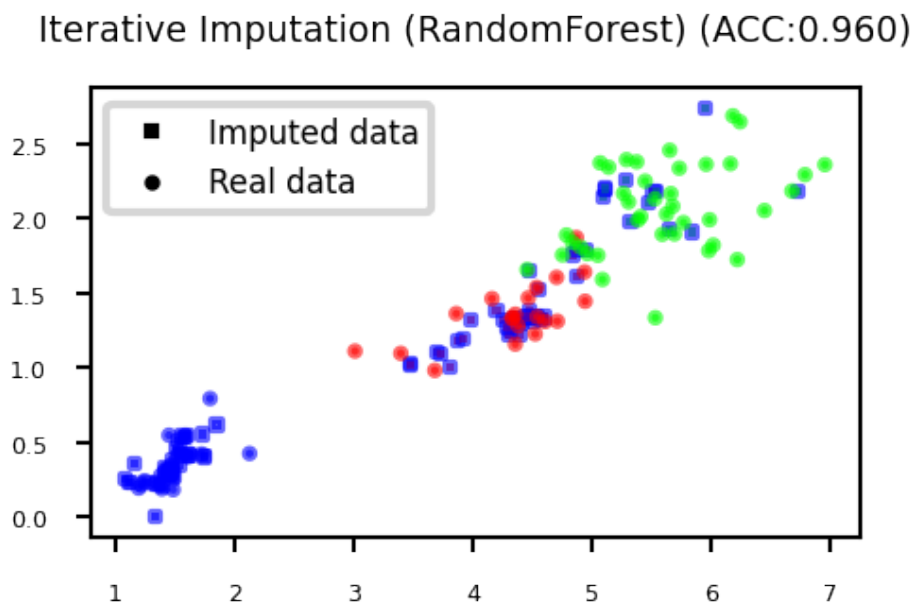
- Same basic idea, but smoother
  - Replace missing values by 0, compute SVD: $\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top$
    - Solved with gradient descent
  - Reduce eigenvalues by shrinkage factor: $\lambda_i = s \cdot \lambda_i$
  - Recompute $\mathbf{X}$: now complete
  - Repeat for m iterations

Soft-thresholded Singular Value Decomposition (SVD) (cont.)



Comparison

- Best method depends on the problem and dataset at hand. Use cross-validation.
- Iterative Imputation (MICE) generally works well for missing (completely) at random data
  - Can be slow if the prediction model is slow
- Low-rank approximation techniques scale well to large datasets



Handling imbalanced data

- **Problem:**
  - You have a majority class with many more examples than the minority class
  - Or: classes are balanced, but associated costs are not (e.g., FN worse than FP)
- **Solutions we've already covered:**
  - Add class weights to the loss function (give minority class more weight)
    - In practice: set `class_weight='balanced'`
  - Change the prediction threshold to minimize false negatives or false positives
- **Preprocessing strategies:**
  - Resample the data to correct the imbalance
    - Random or model-based
  - Generate synthetic samples for the minority class

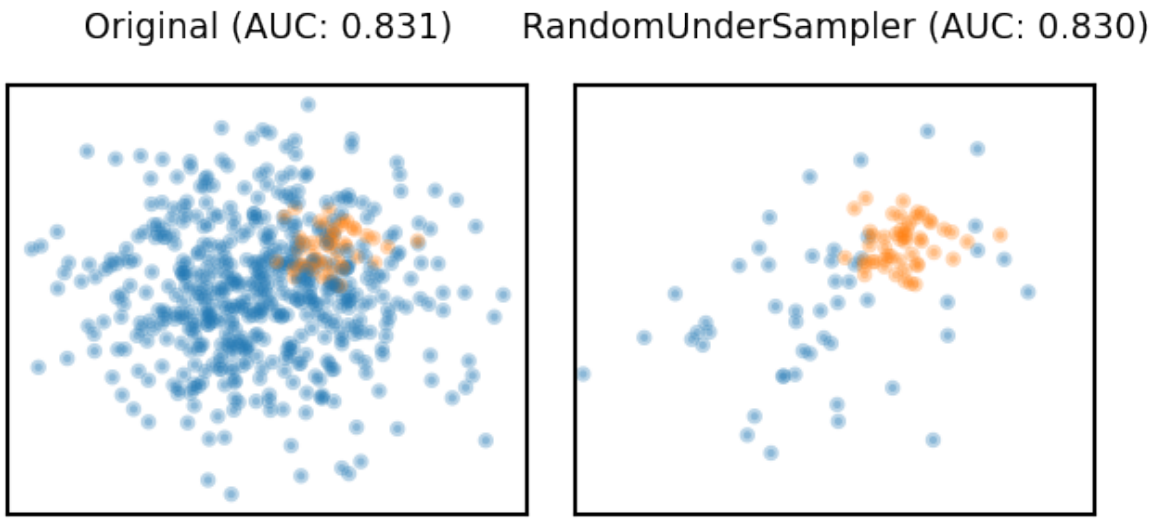
Handling imbalanced data (cont.)

- Build ensembles over different resampled datasets
- Combinations of these

Random Undersampling

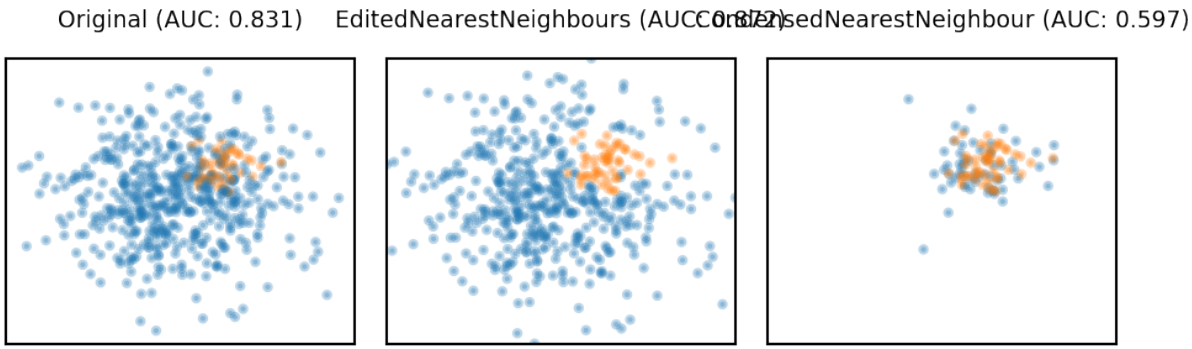
- Copy the points from the minority class
- Randomly sample from the majority class (with or without replacement) until balanced
  - Optionally, sample until a certain imbalance ratio (e.g., 1/5) is reached
  - Multi-class: repeat with every other class
- Preferred for large datasets, often yields smaller/faster models with similar performance

Random Undersampling (cont.)



Model-based Undersampling

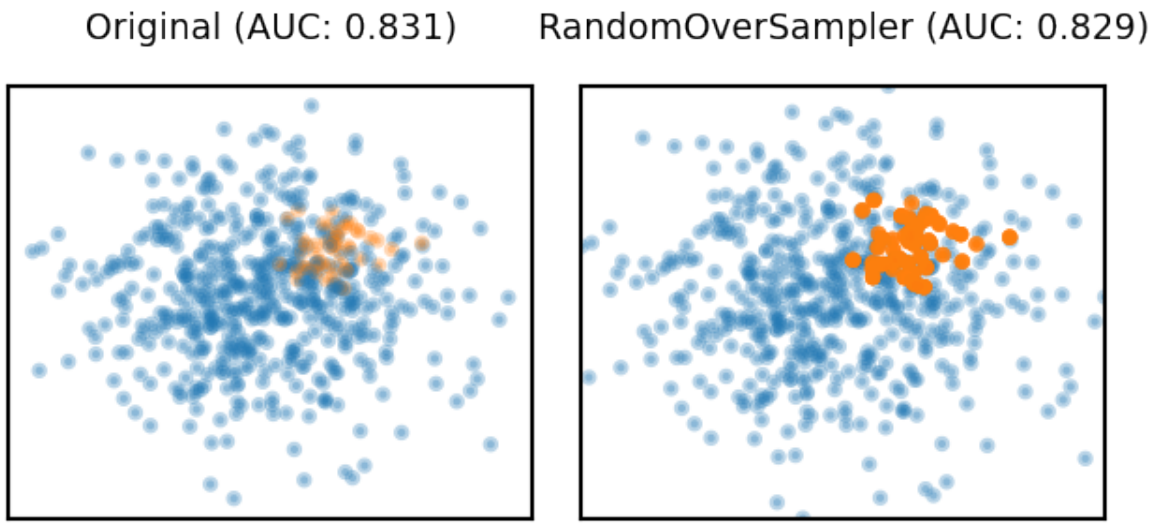
- Edited Nearest Neighbors
  - Remove all majority samples that are misclassified by kNN (mode) or that have a neighbor from the other class (all).
  - Remove their influence on the minority samples
- Condensed Nearest Neighbors
  - Remove all majority samples that are *not* misclassified by kNN
  - Focus on only the hard samples



Random Oversampling

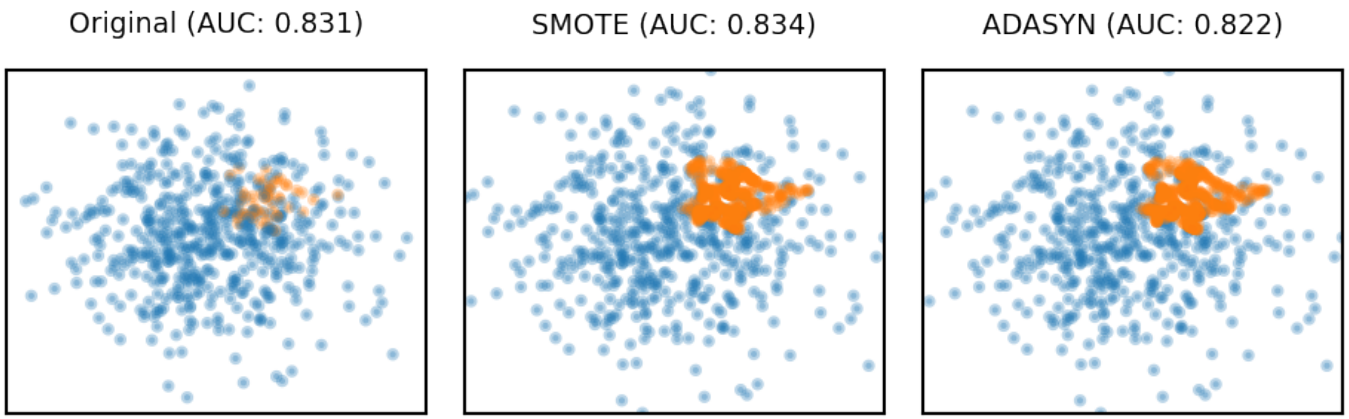
- Copy the points from the majority class
- Randomly sample from the minority class, with replacement, until balanced
  - Optionally, sample until a certain imbalance ratio (e.g. 1/5) is reached
- Makes models more expensive to train, doesn't always improve performance
- Similar to giving minority class(es) a higher weight (and more expensive)

Random Oversampling (cont.)



Synthetic Minority Oversampling Technique (SMOTE)

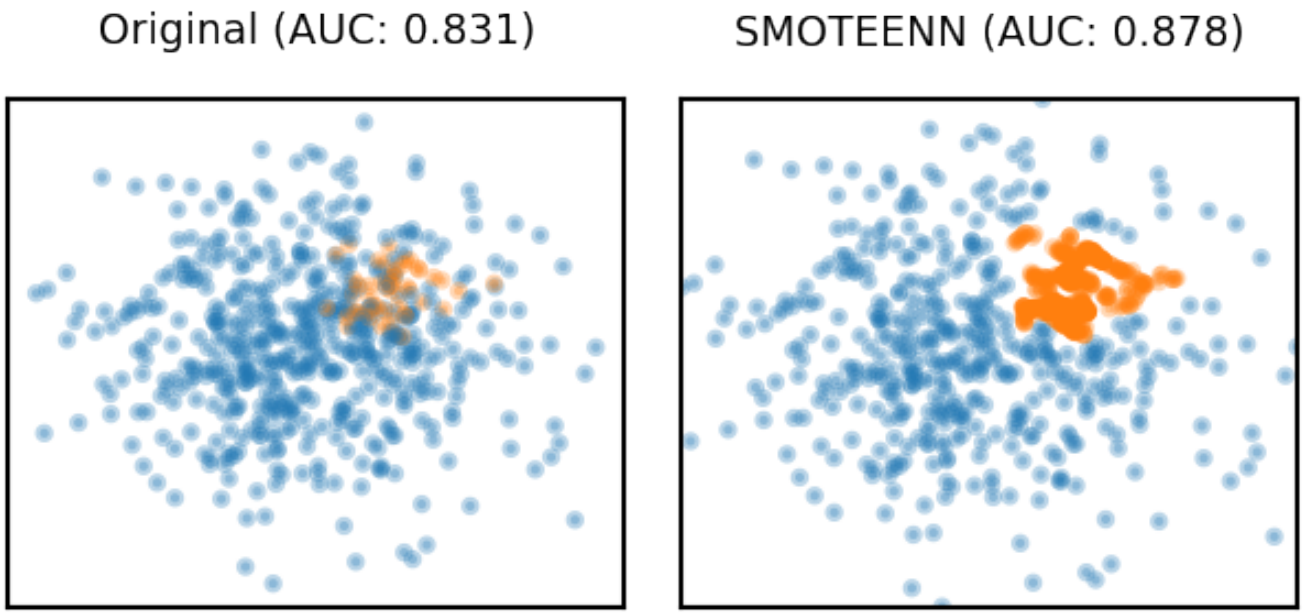
- Repeatedly choose a random minority point and a neighboring minority point
  - Pick a new, artificial point on the line between them (uniformly)
- May bias the data. Be careful never to create artificial points in the test set.
- ADASYN (Adaptive Synthetic)
  - Similar, but starts from 'hard' minority points (misclassified by kNN)



Combined techniques

- Combines over- and under-sampling
- E.g. oversampling with SMOTE, undersampling with Edited Nearest Neighbors (ENN)
  - SMOTE can generate 'noisy' point, close to majority class points
  - ENN will remove up these majority points to 'clean up' the space

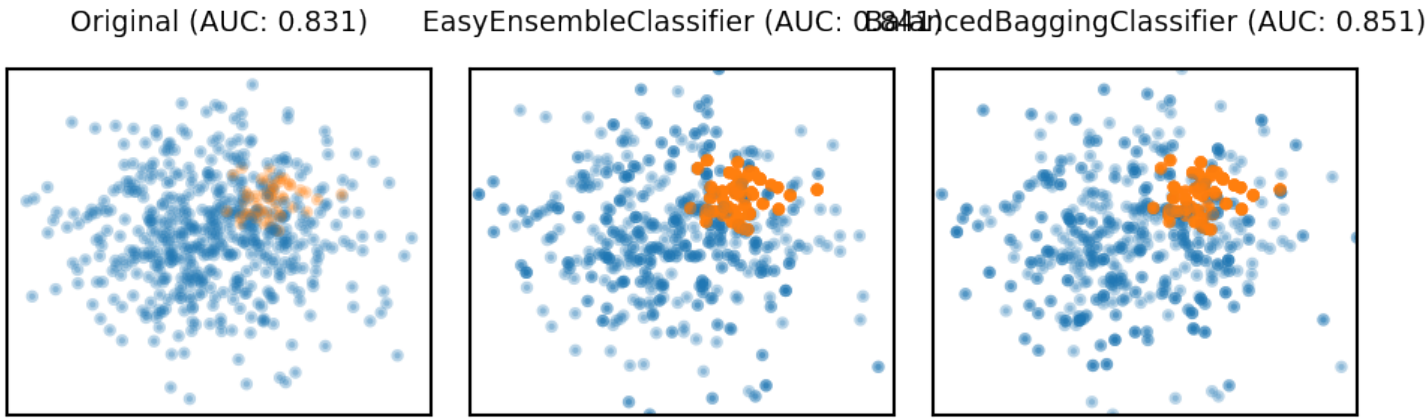
Combined techniques (cont.)



Ensemble Resampling

- Bagged ensemble of balanced base learners. Acts as a learner, not a preprocessor
- BalancedBagging: take bootstraps, randomly undersample each, train models (e.g. trees)
  - Benefits of random undersampling without throwing out so much data
- Easy Ensemble: take multiple random undersamplings directly, train models
  - Traditionally uses AdaBoost as base learner, but can be replaced

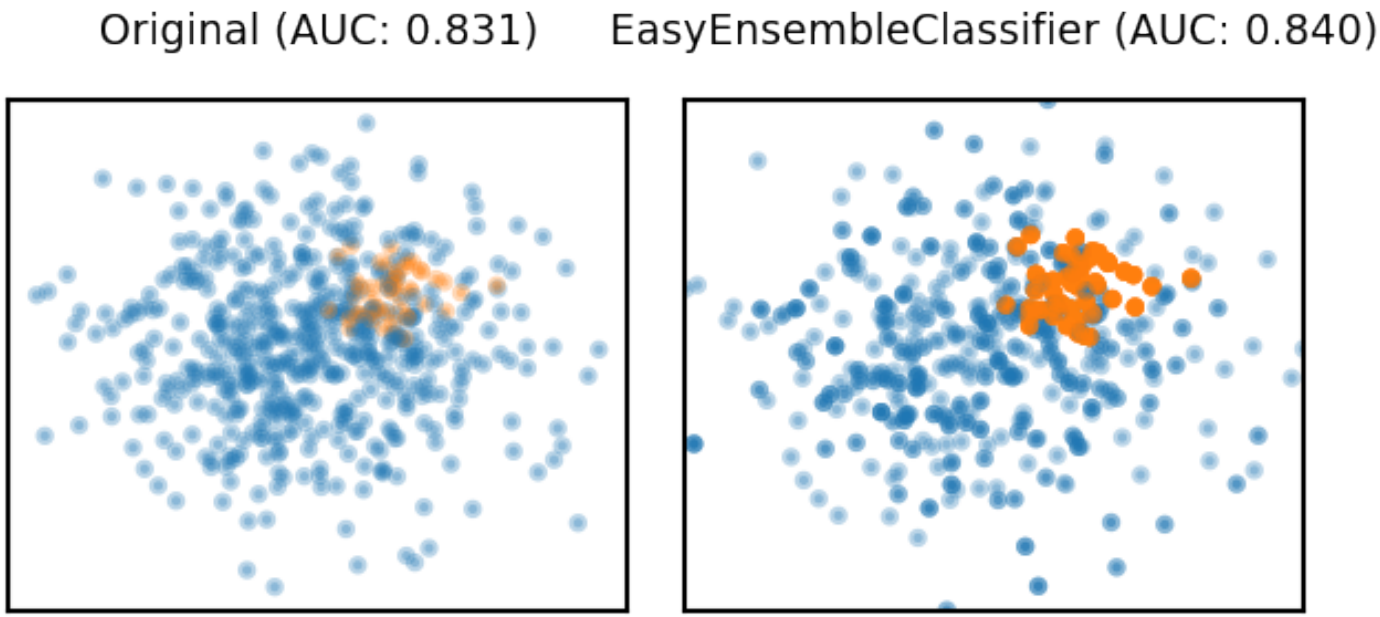
Ensemble Resampling (cont.)



Comparison

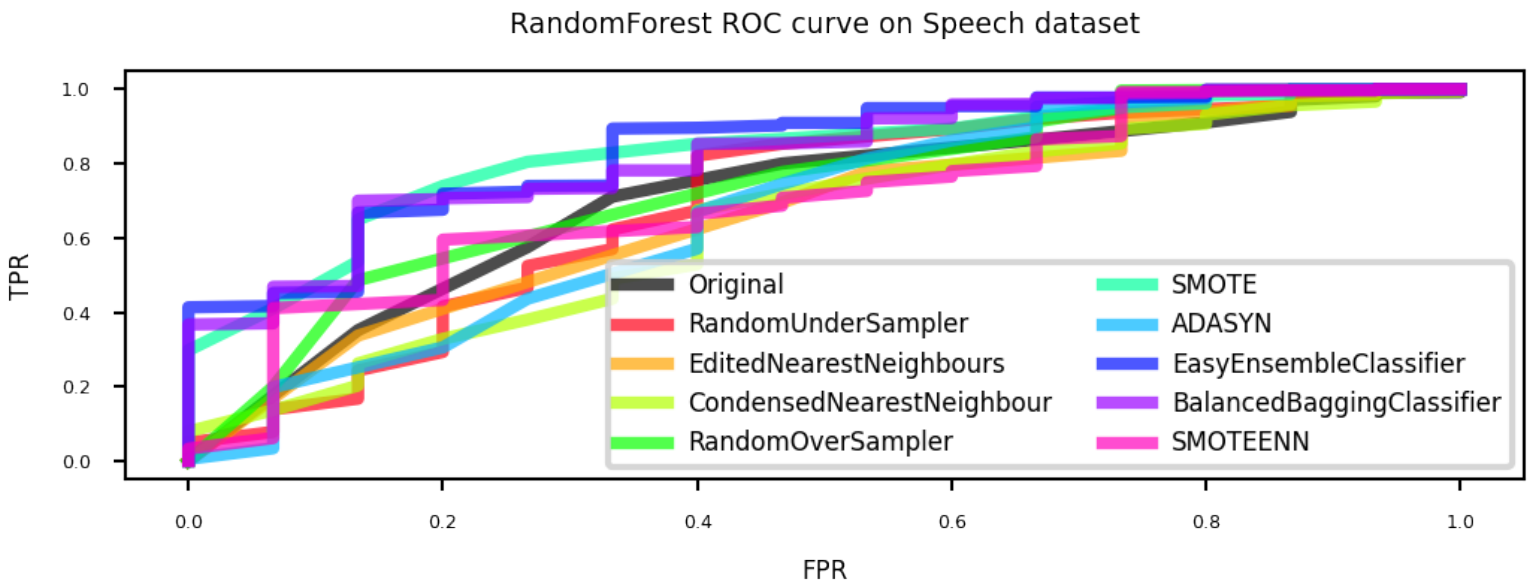
- The best method depends on the data (amount of data, imbalance,...)
  - For a very large dataset, random undersampling may be fine
- You still need to choose the appropriate learning algorithms
- Don't forget about class weighting and prediction thresholding
  - Some combinations are useful, e.g. SMOTE + class weighting + thresholding

Comparison (cont.)



Real-world data

- The effect of sampling procedures can be unpredictable
- Best method can depend on the data and FP/FN trade-offs
- SMOTE and ensembling techniques often work well



Summary

- Data preprocessing is a crucial part of machine learning
  - Scaling is important for many distance-based methods (e.g. kNN, SVM, Neural Nets)
  - Categorical encoding is necessary for numeric methods (or implementations)
  - Selecting features can speed up models and reduce overfitting
  - Feature engineering is often useful for linear models
  - It is often better to impute missing data than to remove data
  - Imbalanced datasets require extra care to build useful models
- Pipelines allow us to encapsulate multiple steps in a convenient way
  - Avoids data leakage, crucial for proper evaluation
- Choose the right preprocessing steps and models in your pipeline
  - Cross-validation helps, but the search space is huge

Summary (cont.)

- Smarter techniques exist to automate this process (AutoML)

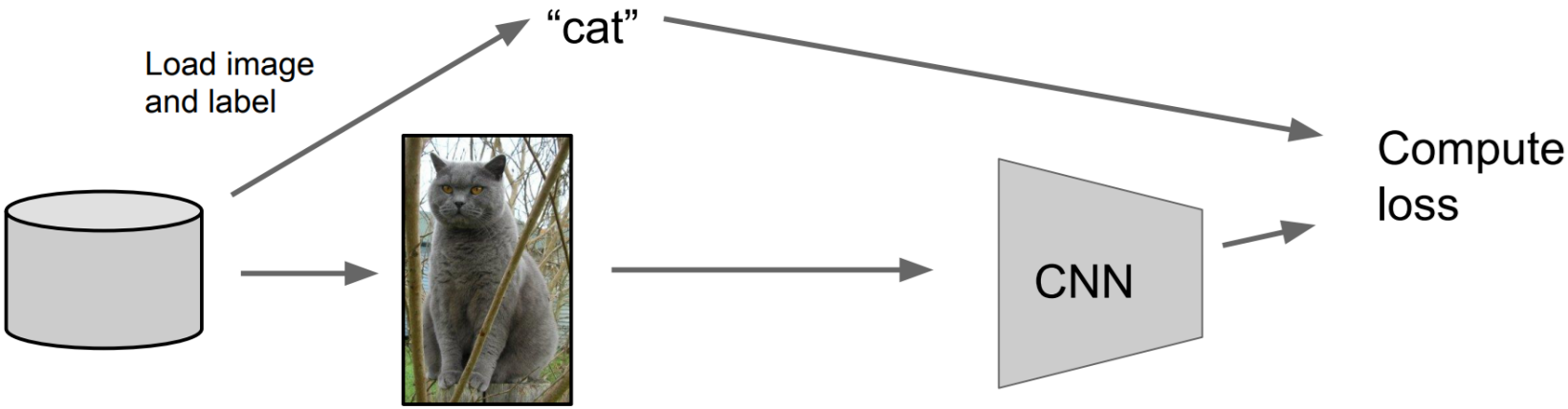
References

[1] Open Machine Learning Course. *Open Machine Learning Course Repository.* GitHub 2024. https://github.com/ml-course/master.

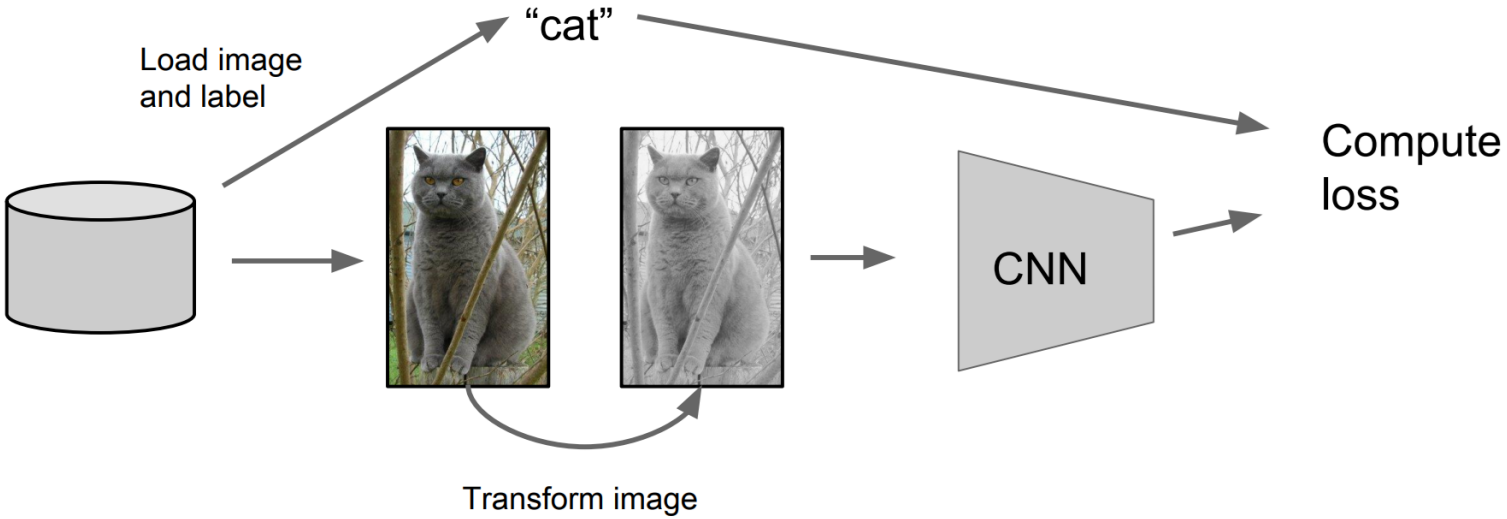
Data Augmentation

- Technique to increase the diversity of training data without collecting new data
- Commonly used in image, text, and audio processing
- Helps reduce overfitting and improve generalization
- Especially useful for deep learning models

Data Augmentation

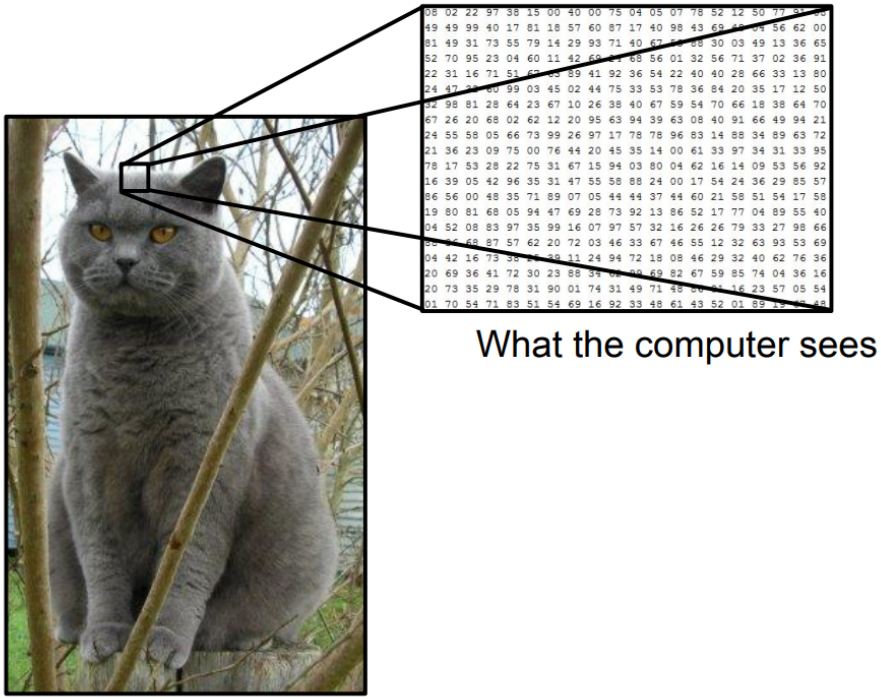


Data Augmentation



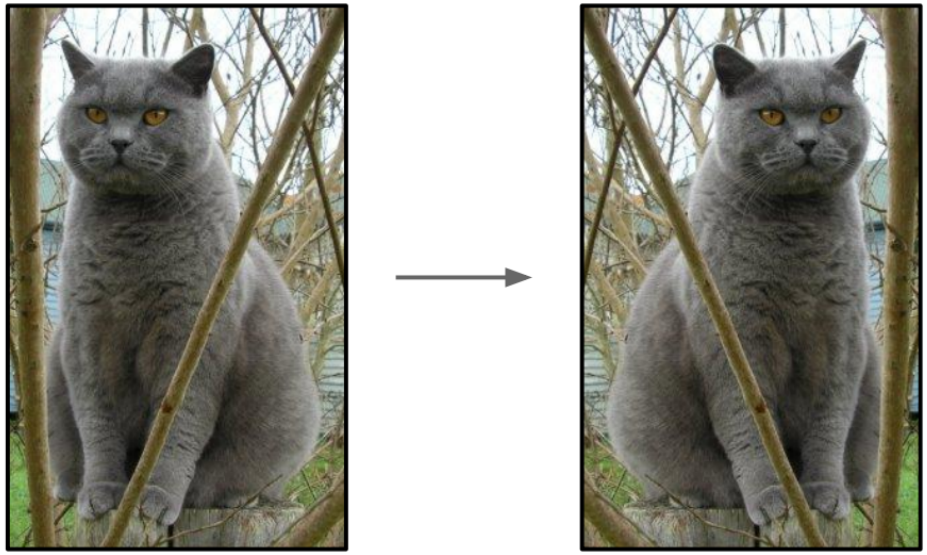
Data Augmentation

- Change the pixels without changing the label
- Train on transformed data
- **VERY** widely used



Data Augmentation

1. Horizontal flips



Data Augmentation

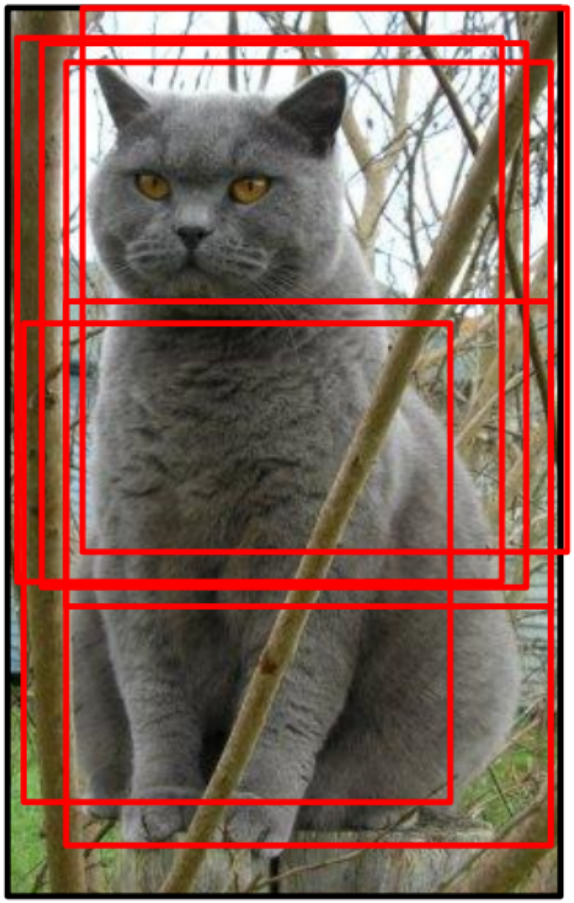
2. Random crops/scales

Training: sample random crops / scales
ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 × 224 patch

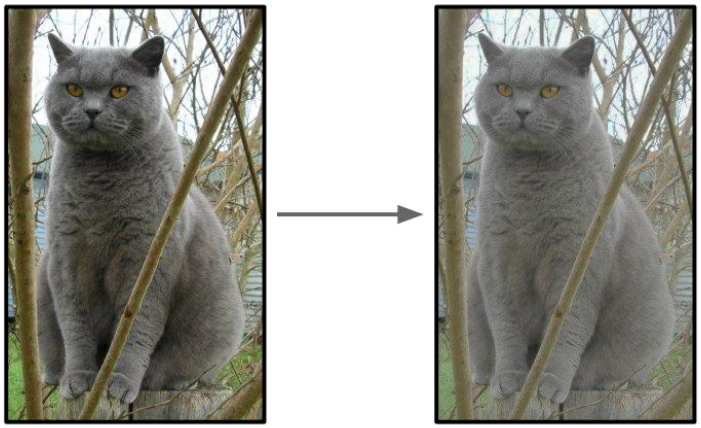
Testing: average a fixed set of crops
ResNet:

1. Resize image at 5 scales: {224, 256, 384, 480, 640}
2. For each size, use 10 224 × 224 crops: 4 corners + center, + flips



3. Color jitter

Simple:
Randomly jitter contrast



Complex:

1. Apply PCA to all [R, G, B] pixels in training set
2. Sample a "color offset" along principal component directions
3. Add offset to all pixels of a training image

(As seen in *[Krizhevsky et al. 2012]*, ResNet, etc)

Data Augmentation

4. Get creative!

Random mix/combinations of:

- translation
- rotation
- stretching
- shearing,
- lens distortions, . . . (go crazy)

Data Augmentation: Takeaway

- Simple to implement, use it
- Especially useful for small datasets
- Fits into framework of noise / marginalization

References

[1] Stanford University. *CS231n: Convolutional Neural Networks for Visual Recognition*. 2024. https://cs231n.stanford.edu/.