Noisy labels

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29 XI 2018

Related terms

- label noise: as anything that obscures the relationship between the features of an instance and its class (Ray J. Hickey, *Noise modelling and evaluating learning from examples*).
- unreliable labels.

Types of noise

- Noisy Completely at random (NCAR).
- Noisy at random (NAR): probability of incorrect class dependes on the true class.
- Noit not at random (NNAR): probability of incorrect class depends on the on true class and features.

Consequences

Label noise is known to

- decrease model performance,
- increase model complexity.

Dealing with noise

1. Robust models
    - specialized models (e.g. logistic regression with noise label-correction),
    - choice of model hyper-parameters (e.g. split criterion in decision trees).

Dealing with noise

2. Data Cleansing
    - anomaly and outlier detection,
    - influential observations,
    - removing misclassified instances,
    - kNN-based methods,
    - voting filtering

Identifying and Eliminating Mislabeled Training Instances

Identifying Mislabeled Training Data Brodley, C. E., & Friedl, M. A. (1999). Journal of Artificial Intelligence Research, 11, 131–167.

- The approach employs an ensemble of classifiers that serve as a filter for the training data.
- The idea: using a set of classifiers formed from part of the training data to test whether instances in the remaining part of the training data are mislabeled.
- m learning algorithms, n-fold cross-validation
- consensus vote - all classifier must agree

Dealing with noise

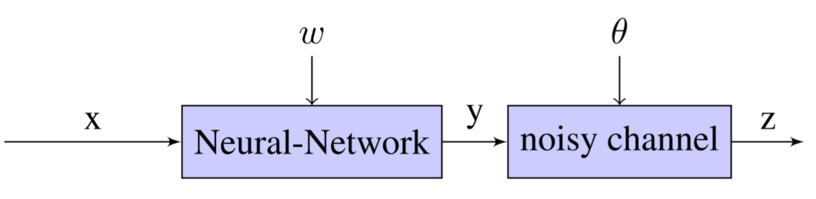
3. Removing just the labels (turns the problem into semi-supervised, example of semi-sup: The R Package bgmm: Mixture Modeling with Uncertain Knowledge)
4. Probabilistic frameworks

Training deep neural-networks based on unreliable labels

Training deep neural-networks based on unreliable labels. Bekker, A. J., & Goldberger, J. (2016). In 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).

- multi-class neutral-network
- adding extra noise layer by assuming that the observed labels were created from the true labels by passing through a noisy channel whose parameters are unknown

Training deep neural-networks based on unreliable labels



- Since the random variables y_i are hidden, we apply the EM algorithm to find the maximum-likelihood parameter set.

Applications to microarrays

Detecting potential labeling errors in microarrays by data perturbation, Andrea Malossini, Enrico Blanzieri, Raymond T. Ng (2006).

- A Matrix called LOOPC (Leave-One-Out Perturbed Classification) is built: LOOPC[i, j] is the result of flipping the label of x_i and leaving x_j out of the sample.
- LOOPC[i,]: predictions of different observations based on the same dataset (x_i removed).
- LOOPC[, j]: predictions for x_j based on different datasets.
- Column analysis: classification stability algorithm. Correctly labeled samples should be classified consistently despite small perturbations.
- Row analysis: Leave-One-Out-Error-sensitivity algorithm. If an observation is mislabeled, flipping the label should improve model performance.

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