Missing features

What if our data is not perfect ?

What do we do about examples with missing features

- training examples
- test exammples

We have thus far being treating this as an annoyance

- problem is important
- far from simple

The simplest thing to do would be to drop the example

- can't do it with a test example
- reduces amoung of data in training

We could alternatively, drop the feature entirely

- the features missing among several examples may be disjoint

Either way, losing training data is not desirable, particularly for small datasets

- We will motivate the problem and illustrate the issues
- We will examine naive solutions
    - almost always bad !
- We will show an interesting solution using Random Forests
- Preview of clustering methods

The term **imputation** refers to creating a substitute for the missing value of a feature in one example.

To frame our discussion

Let

- Let f denote the index of a feature
- $\mathbf{x}^{(m')}$ be an example (either training or test) with missing feature $\mathbf{x}_f^{(m')}$
- $\hat{\mathbf{x}}^{(m')}$ be the imputed valued for $\mathbf{x}^{(m')}$

As usual let $\mathbf{X}, \mathbf{y}$ be our labelled training examples.

$$\{(\mathbf{x^{(i)}}, \mathbf{y^{(i)}}) | 1 \leq i \leq m\}$$

Naive methods for imputation

Magic numbers

Let's start with a truly awful method: set $\hat{\mathbf{x}}_f^{(m')}$ to a "magic number"

- 0
- -999

Why is the magic number awful ?

Consider a training set representing the population of NYC, with features Weight, Height, Age, etc.

Suppose Weight, which is at index f of example vector $\mathbf{x}^{(m')}$ is missing.

Setting $\hat{\mathbf{x}}_f^{(m')} = 0$ is awful because the imputed value is not likely

- $p(\mathbf{x}_f^{(m')} = 0) \approx 0$

Mean, median, percentile

How about something more likely, like the mean or median ?

Better

- $p(\mathbf{x}_f^{(m')} = \bar{\mathbf{x}}_f) > 0$

Still not perfect.

- What if $p(\mathbf{x}_f)$ were a bi-modal distribution
    - lots of examples with extreme values, few in the middle

So mean and median are better than magic numbers in many situations but not all.

Even worse:

Suppose example $\mathbf{x}^{(m')}$ is an infant: is $\bar{\mathbf{x}}_f$ still reasonable ?

- $p(\mathbf{x}_f^{(m')} = \bar{\mathbf{x}}_f | \mathbf{x}_{\text{Age}}^{(m')} < 1) \approx 0$

So the mean, median etc.

- provides a reasonable imputation in a univariate sense
- provides a less reasonable imputation in a multivariate sense
    - conditional on other features like Age

Imputation depends on how the imputed value is used

Less obvious is that $\hat{\mathbf{x}}_f^{(m')}$ will be used for training some model.

So perhaps we should consider how the model that we are going to fit uses $\hat{\mathbf{x}}_f^{(m')}$.

To illustrate, suppose the model uses the dot product to measure similarity among examples

- a variant of KNN

Knowing this, we can show that different choices of $\hat{\mathbf{x}}_f^{(m')}$ influence the similarity metric.

In [6]:

```
df

print("A vs B")
compare_subs(A,B)

print("A vs C")
compare_subs(A,C)
```

Out[6]:

	a	d	e	b	c	f
A	4.0	5.0	1.0	NaN	NaN	NaN
B	5.0	NaN	NaN	5.0	4.0	NaN
C	NaN	2.0	4.0	NaN	NaN	5.0

```
A vs B
        Substitute 0: similarity= 0.38
        Substitute w/feature mean: similarity= 0.94
        Center, then Substitute 0: similarity= 0.09
A vs C
        Substitute 0: similarity= 0.32
        Substitute w/feature mean: similarity= 0.87
        Center, then Substitute 0: similarity= -0.56
```

- A versus B
    - missing values are paired against relatively high values
        - Substituting 0 (a low value) reduces similarity
        - Substituting mean (a relatively high value) increase similarity
            - A is a tougher rater: A.mean() < B.mean()
    - in the end, A and B had only a *single* true point of comparison ("a")
        - you made up the similarity
- A versus C:
    - *NO* feature "a" in common !
    - But at least A and B are closer than A and C for some substitutions

Cosine similarity

- is a *scale dependent* measure
    - so centering, scaling matter
    - Analogy
        - difference between Covariance and Correlation
            - Correlation is Covariance of normalized (scaled) variables

The choice of $\hat{\mathbf{x}}_f^{(m')} = 0$ is **not** neutral if the data is not centered

- e.g., if 0 is the minimum of $\mathbf{x}_f$, rather than the average

Predictive methods for imputation

Hopefully the preceding examples illustrated some issues in imputation.

Can we do better ?

Let $\mathbf{x}_{\bar{f}}$ denote the vector of features *excluding* the one at index f.

We can frame the imputation problem as finding

$$p(\mathbf{x}_f^{(m')} | \mathbf{x}_{\bar{f}}^{(m')})$$

That is: find likely values for the missing feature, *given* values for the non-missing features.

How do we do this ?

Machine Learning to the rescue !

- fit a model on the subset of training examples
    - that *have* feature f (used as target)
- use the model to predict $\hat{\mathbf{x}}_f^{(m')}$

Simple predictive imputation

Some ideas

- Naive Bayes
  - Assumption of distribution of features can compensate for missing features
- Regression
  - $\mathbf{x}_f = \Theta^T \mathbf{x}_{\bar{f}}$
    - feature f as a function of the other features
  - $\mathbf{x}_f = \Theta^T \mathbf{z}$
    - $\mathbf{z}$ may be features, not present in $\mathbf{x}$, that are believed to be correlated with $\mathbf{x}_f$

Proximity based imputation

A proximity based method

- creates a proximity (opposite of distance) measure $prox(\mathbf{x}^{(m')}, \mathbf{x}^{(\mathbf{i})})$ between $\mathbf{x}^{(m')}$ and training example $\mathbf{x}^{(\mathbf{i})}$
- $\hat{\mathbf{x}}_f^{(m')}$ is the proximity weighted average of the values of the feature in the training set

$$\hat{\mathbf{x}}_f^{(m')} = \sum_{i=1, i \neq m'}^{m} prox(\mathbf{x}^{(m')}, \mathbf{x}^{(\mathbf{i})}) \mathbf{x}_f^{(\mathbf{i})}$$

That is

- the missing value should be similar to the feature value in training examples "similar" to $\mathbf{x}^{(m')}$.

The definition of proximity (similarity) will vary.

Note

For categorical $\mathbf{x}_f^{(m')}$ use the most frequent non-missing value

- where the frequency is weighted by proximities.

The method works for multiple missing features but we illustrate with a single one for simplicity.

Limitations

For the imputation of

$$p(\mathbf{x}_f^{(m')}|\mathbf{x}_{\bar{f}}^{(m')})$$

we are implicitly assuming that if feature vectors $\mathbf{x^{(i)}}, \mathbf{x}^{(i')}$ are "similar" then so are their targets

$$\mathbf{y^{(i)}} \approx \mathbf{y}^{(i')}$$

With that limitation in mind there are related methods

- Clustering
    - find groups of examples with common features
        - K-means
    - PCA, Recommender systems
        - Unsupervised Machine Learning: Preview of coming lecture !

Random Forest proximity method for missing data

There is an interesting method for using a Random Forest to impute missing data.

It is interesting because proximity is determined by both the features *and* the target so we are modeling

$$p(\mathbf{x}_f | \mathbf{y}, \mathbf{x}_{\bar{f}})$$

That is, it fits a model of $\mathbf{x}_f$ given the features other than f **and** the target.

A test example with missing features doesn't have a target; we will see how this method adapts.

Missing feature in Training example

We will use a Random Forest to define a proximity measure.

Missing Value Imputation using Random Forest (https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm#missing1)

- Initialization
  - Set $\hat{\mathbf{x}}_f^{(m')}$ to a "reasonable" guess
    - Continuous: mean, median
    - Categorical: most frequent
  - Create the initial Random Forest $F_{(0)}$

- Iteration i:
    - Define the proximity to example $\mathbf{x^{(i)}}$
        - $prox(\mathbf{x}^{(m')}, \mathbf{x^{(i)}}) = \#$ of trees in $F_{(i-1)}$ with $\mathbf{x}^{(m')}$, $\mathbf{x^{(i)}}$ in same leaf
    - Update imputed value $\hat{\mathbf{x}}_f^{(m')}$

$$\hat{\mathbf{x}}_f^{(m')} = \sum_{i=1}^{m} prox(\mathbf{x}^{(m')}, \mathbf{x^{(i)}}) \mathbf{x_f^{(i)}}$$

    - Create next Random Forest $F_{(i)}$

Iterate until convergence.

The authors suggest 4-6 iterations suffice.

Missing feature in Test example

Method similar to that for a missing feature in a Training example, once we deal with a crucial difference

- there is **no label** for the test example (that's what we're trying to predict)

Suppose the classification target $\mathbf{y} \in C$ (i.e., the possible labels)

$$C = \{c_k | 1 \leq k \leq |C|\}$$

- For each $c \in C$:
  - $\hat{\mathbf{x}}_{f,c}^{(m')}$ is the imputed value obtained from the above by assuming $\mathbf{y}^{(m')} = c$
    - that is, run the missing feature for training algorithm assuming label of $\mathbf{x}^{(m')}$ is c

We now have one imputed value $\hat{\mathbf{x}}_{f,c}^{(m')}$ and final Random Forest per class c.

Which one do we choose ?

Observe that the c^{th} Random Forest *should* predict class c given input $\mathbf{x}^{(m')}$ since we set $\mathbf{y}^{(m')} = c$

So we choose the forest and imputed value $\hat{\mathbf{x}}_{f,c}^{(m')}$

- from the class c in which $\mathbf{x}^{(m')}$ is most often classified as being in class c.

Now casting

The field of economic forecasting encounters a problem similar to missing data

- many economic indices are combinations of sub-indices
    - sub-indices published at different frequencies
    - sub-indices published on different days

The "total" index can't be computed until **all** sub-indices have been released.

So with respect to an "early" publication date, some sub-index data is missing.

Now-casting (a play on "forecasting") uses techniques to make early predictions of sub-index values

In some cases they use features $\mathbf{z}$ believed to be correlated with actual features $\mathbf{x}$:

- derive higher frequency values for low frequency data (annual GDP, monthly Manufacturing)
    - National Manufacturing employment may be highly correlated to Employment in a few states
        - state-level employment may be published
            - at higher frequency
            - earlier date
        - Many of these low frequency features are *composites* of other features
        - some elements of the composite are released before others
            - may predict the whole
        - Now-casting site (https://www.now-casting.com/home)

Missing data imputation in `sklearn`

- `SimpleImputer`, `IterativeImputer` (https://scikit-learn.org/stable/modules/impute.html)
- `IterativeImputer` with different regression estimators (https://scikit-learn.org/stable/auto_examples/impute/plot_iterative_imputer_variants_comparisc

In [7]:
```
print("Done")
```

```
Done
```