Some heuristics for missingness

Quinn Dougherty
Lambda School

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About me

Quinn Dougherty

Philadelphia

Teaching assistant - Lambda School

Interviewing

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Assumptions

I’m assuming you know what this means 👉

I’m assuming you’ve filled

with column-mean at least once

I’m assuming some Pandas syntax

```
print("missing rate by feature: ")
(titanic_.isna().sum() / titanic_.shape[0])
```

```
missing rate by feature:
PassengerId       0.0 %
Survived          0.0 %
Pclass            0.0 %
Name              0.0 %
Sex               0.0 %
Age             19.87 %
SibSp             0.0 %
Parch             0.0 %
Ticket            0.0 %
Fare              0.0 %
Cabin            77.1 %
Embarked       0.2245 %
dtype: object
```

What the talk is not

- Advanced imputation workshop
- Intermediate imputation workshop
- expert

What the talk is

- Overview of strategies that might point you toward wise experimentation

Imputation

*In statistics, **imputation** is the process of replacing missing data with substituted values.*

- Wikipedia

Missingness regimes

We classify missingness into three different *regimes*

1. Missingness of a feature is a function of itself
2. Missingness of a feature is a function of all other features
3. Missingness of a feature is “truly random”

Missingness regimes - technical terms

We classify missingness into three different *regimes*

1. Missingness of a feature is a function of itself
   a. *MNAR: Missing Not At Random*
2. Missingness of a feature is a function of other features
   a. *MAR: Missing At Random*
3. Missingness of a feature is “truly random”
   a. *MCAR: Missing Completely At Random*

Missingness regimes - how do I know?

We classify missingness into three different *regimes*

1. Missingness of a feature is a function of itself
   a. *MNAR: Missing Not At Random*
   b. Domain knowledge >> statistical tests
2. Missingness of a feature is a function of other features
   a. *MAR: Missing At Random*
   b. Domain knowledge >> statistical tests
3. Missingness of a feature is “truly random”
   a. *MCAR: Missing Completely At Random*
   b. Domain knowledge >> statistical tests

MNAR: Missing Not at Random

Missingness of a feature is a function of itself

- Domain knowledge, data collection methodology
- Absent a common-sensical insight, you can't prove MNAR, but you can show that it's not MAR or MCAR (Eekhout, 2014).
- *Example:* Someone is collecting height data by having people write down their height on a drop of paper and dropping it in a box, which is 9 feet above the ground

MAR: Missing at Random

Missingness of a feature is a function of other features.

find some $f_i := (X_k \mid k \text{ in } 1..n) \mapsto \text{filled}(X_i)$

Observe correlations of the indicator matrix - strong correlations is one reason to suspect MAR

```
titanic_.isna().corr()
```

MAR: Missing at Random

Missingness of a feature is a function of other features.

You can also target a feature's indicator function in a logistic regression, strong coefficients suggest MAR.

$$\texttt{df.Xi.isna()} \cong \texttt{sigmoid(X } \beta\texttt{)}$$

MAR: Missing at Random -- ok, then what?

Missingness of a feature is a function of other features.

MAR suggests that you should try **multivariate imputation**

- Python: `fancyimpute.IterativeImputer`
- R: `MICE` (Multivariate Imputation by Chained Equations)

But again-- experiment and commonsense prevail over heuristics

MCAR: Missing Completely at Random

Missingness of a feature is “truly random”

It’s seductive to fall back on this, but not as likely as you think (Niederhut, 2018)

MCAR: Missing Completely at Random -- a brief study

Missingness of a feature is “truly random”

We can easily simulate this case with a bernoulli variable

```
def mcar_goblin(dat: DataFrame, ratio: float) -> DataFrame:
    ''' Simulate MCAR with bernoulli '''
    def ident_or_nan(x: float) -> float:
        ''' if heads, replace value with nan. if tails, identity '''
        coin = bernoulli(ratio)
        if coin.rvs()==1:
            return nan
        else:
            return x

    return dat.assign(**{feat: [ident_or_nan(x)
                                for x in dat[feat].values]
                         for feat in dat.columns if feat!='y'})
```

MCAR: Missing Completely at Random -- a brief study

Missingness of a feature is “truly random”

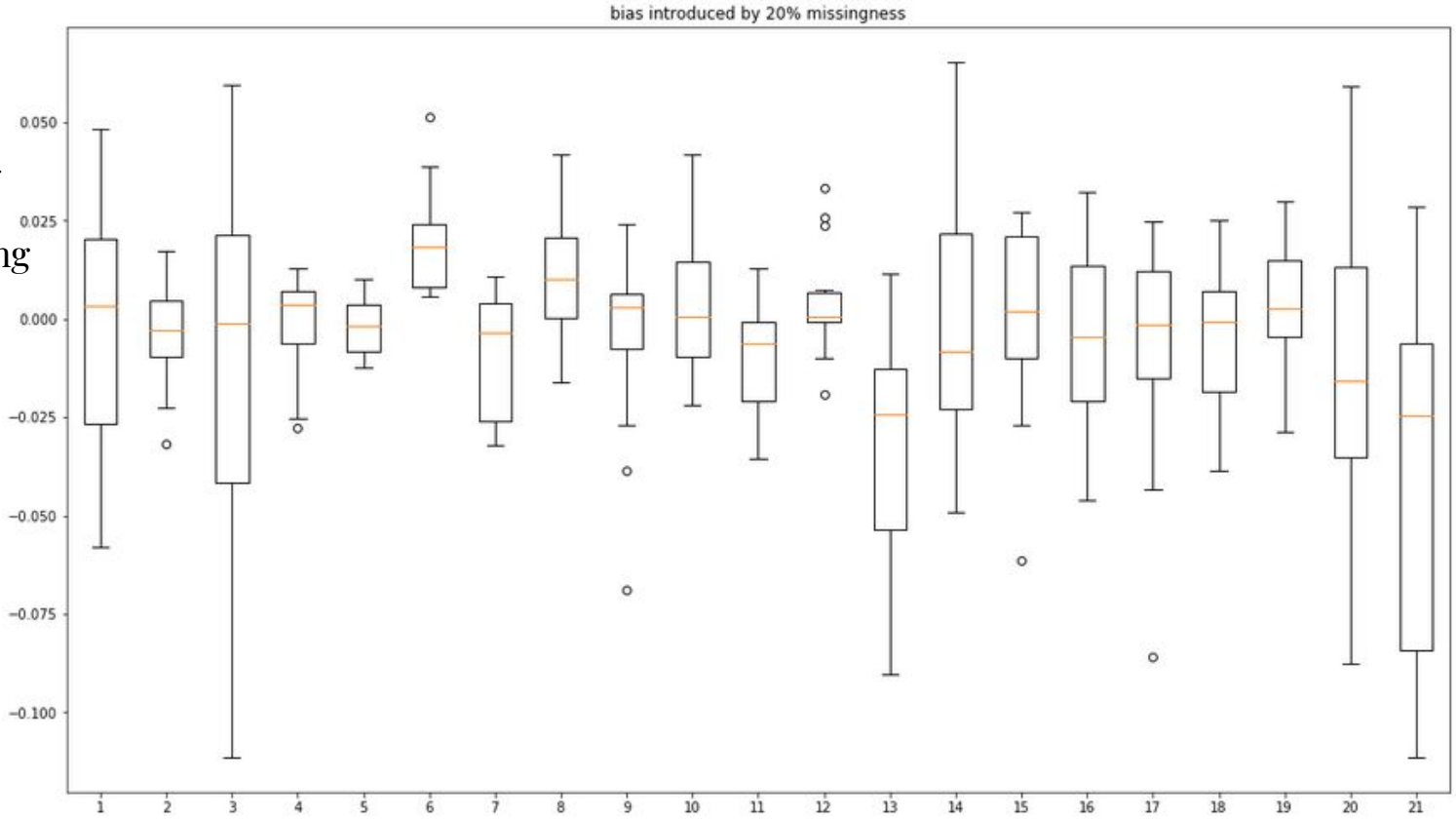
Train a model on complete data and then train a pipeline with an imputer on data that the goblin has interfered with.

Observe the *differences* in coefficients to see the **bias** of imputation and missingness, over several imputation methods.

Dataset is DrivenData’s Tanzanian Waterpoints competition

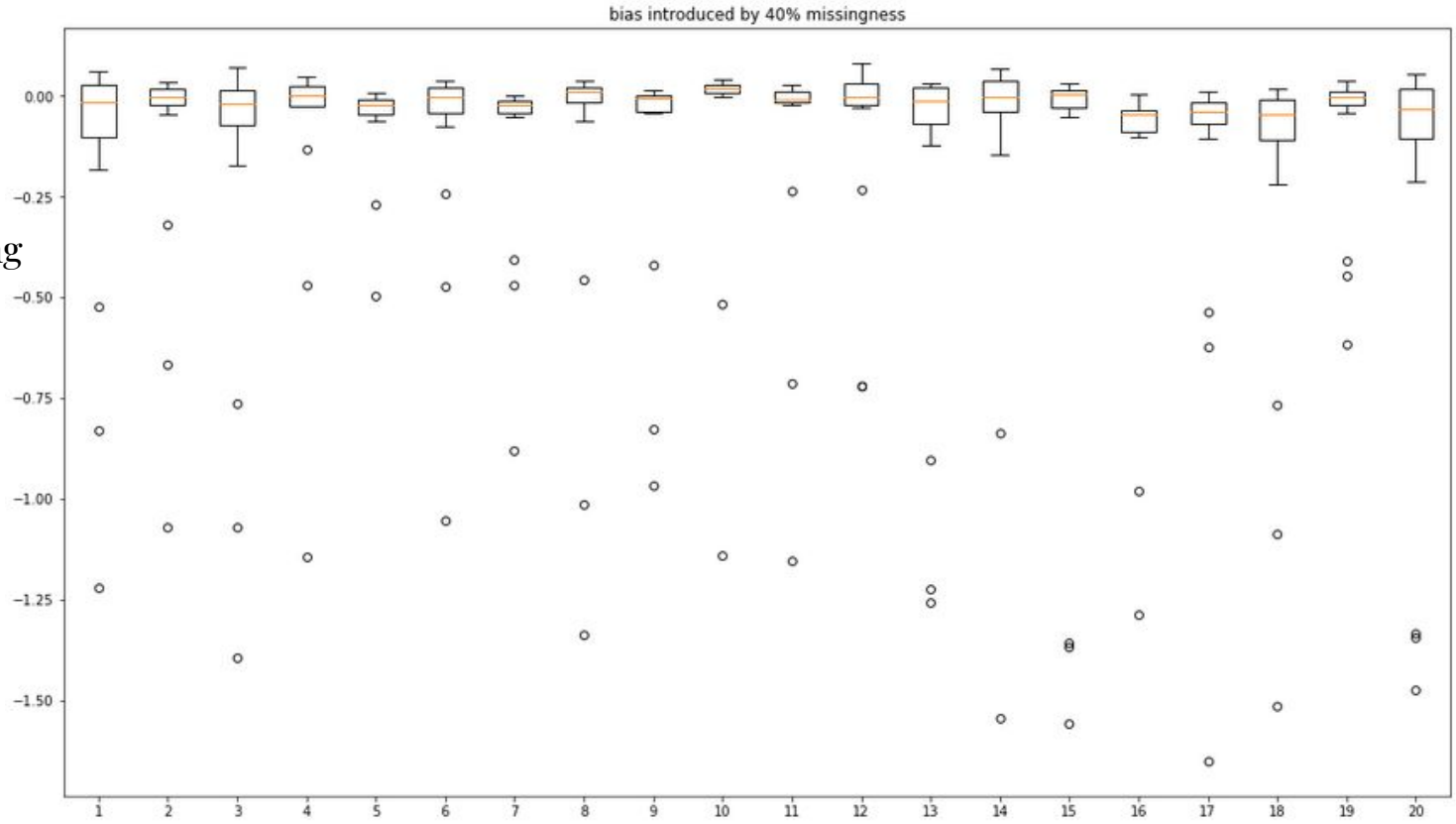
MCAR: Missing Completely at Random -- a brief study

Bias introduced by 20% missing



MCAR: Missing Completely at Random -- a brief study

Bias introduced by 40% missing



Summary

Imputation is finding values to fill in missingness with

It introduces bias

There are different ways it can be missing (MNAR, MAR, and MCAR)

Experiment, commonsense, and domain knowledge >> statistical tests

Sources

https://github.com/deniederhut/safe-handling-instructions-for-missing-data

https://www.iriseekhout.com/missing-data/

https://pypi.org/project/fancyimpute/

Thank you

Quinn Dougherty
quinndougherty92@gmail.com
/in/quinn-dougherty/