ANOMALY DETECTION

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RESOURCES

```
Numpy:                          pip install numpy
Pandas:                         pip install pandas
TDDA library:                   pip install tdda
Feather format:                 pip install feather-format
Enhancements for
   feather format:              pip install pmmif

Material for workshop (inc slides):

git clone \
    https://github.com/tdda/pydatalondon2018ad.git

Docs: tdda library: http://tdda.readthedocs.io

TDDA generally:     http://tdda.info
```

PART I:

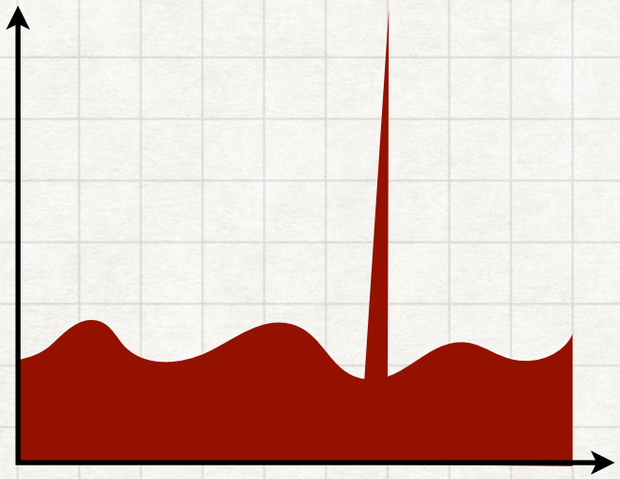
CONCEPTS

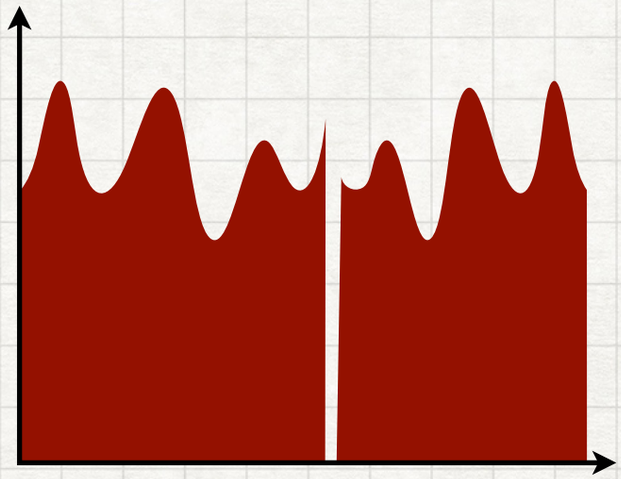
WHAT IS ANOMALY DETECTION?

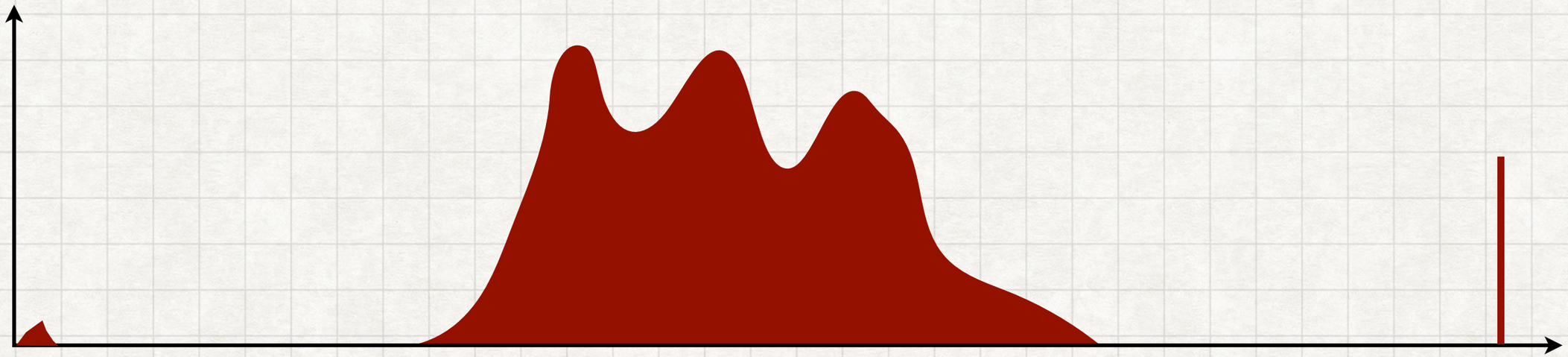
- Anomaly: Deviation from “normal” / “expected”
  - Intrinsically dependent on expectation / definition of normality
- Examples:
  - Detect problems, e.g. fraudulent credit card transactions, systems failures (e.g. server down), gaming (e.g. bogus ecommerce ratings), medical problems (e.g. heart arhythmia).
  - Also, detect opportunities: buying patterns suggesting new markets / offers, low usage periods suggesting savings, identifying unusually successful staff / methods / approaches etc.

WHAT ANOMALIES LOOK LIKE (CONCEPTUALLY)

Outlying values in One Dimension



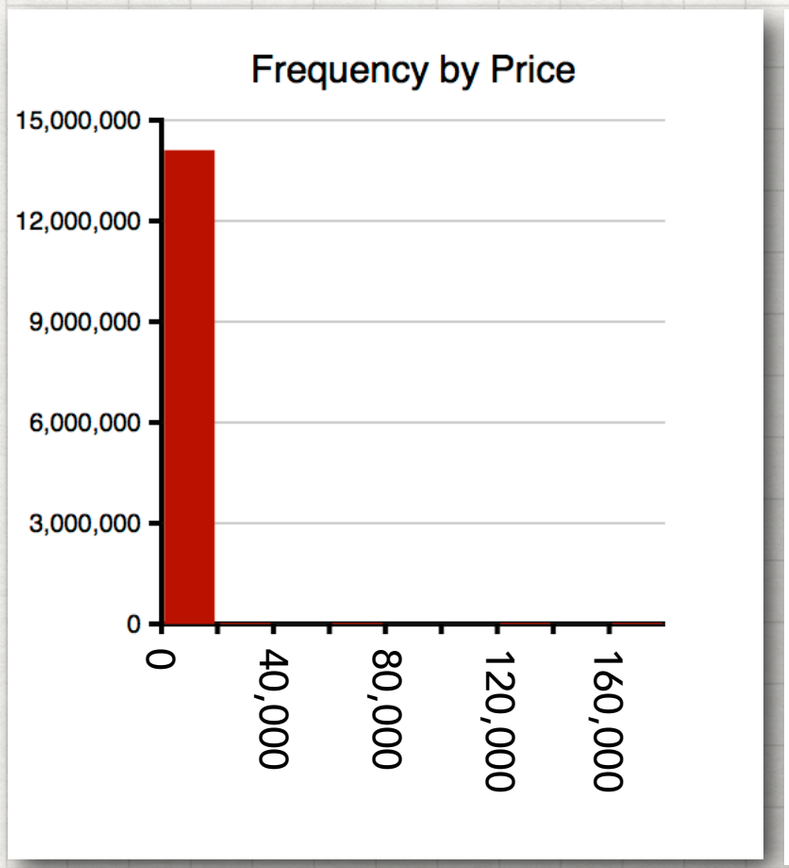




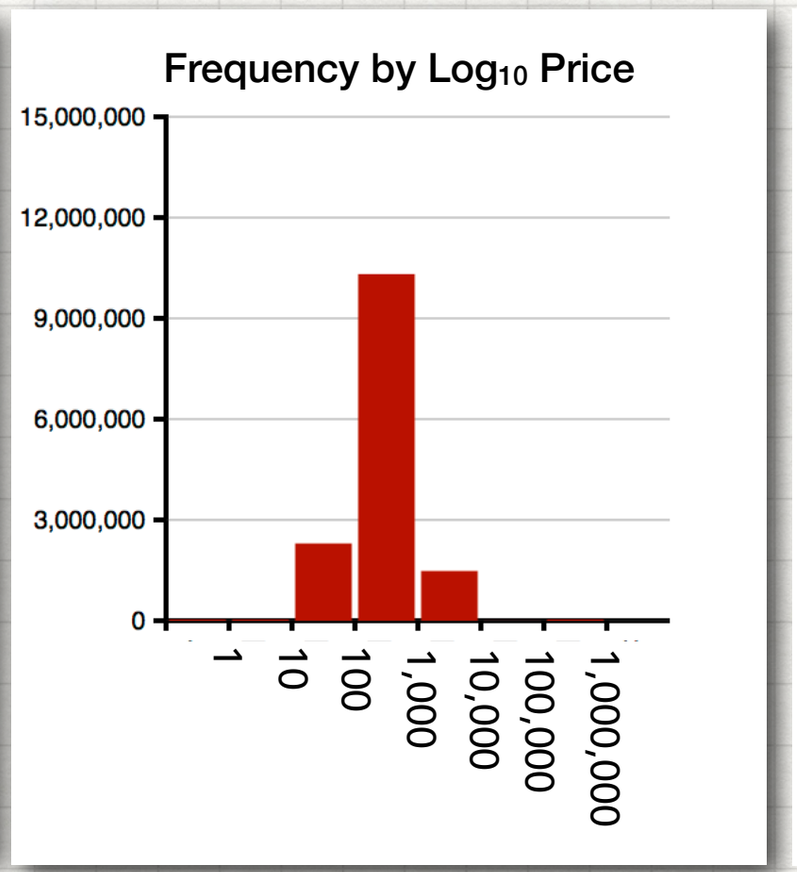
Often much more extreme than shown here, making plotting tricky

WHAT ANOMALIES OFTEN LOOK LIKE IN PRACTICE

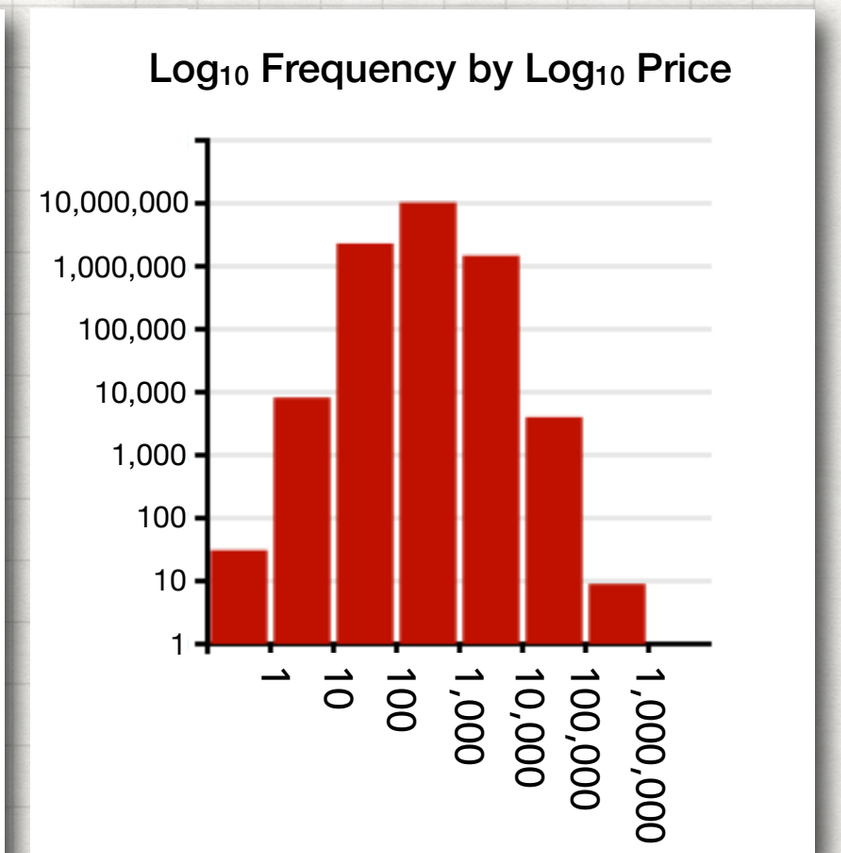
Using Logarithmic or Log-Log Plots to Display Outliers can help



Linear Histogram



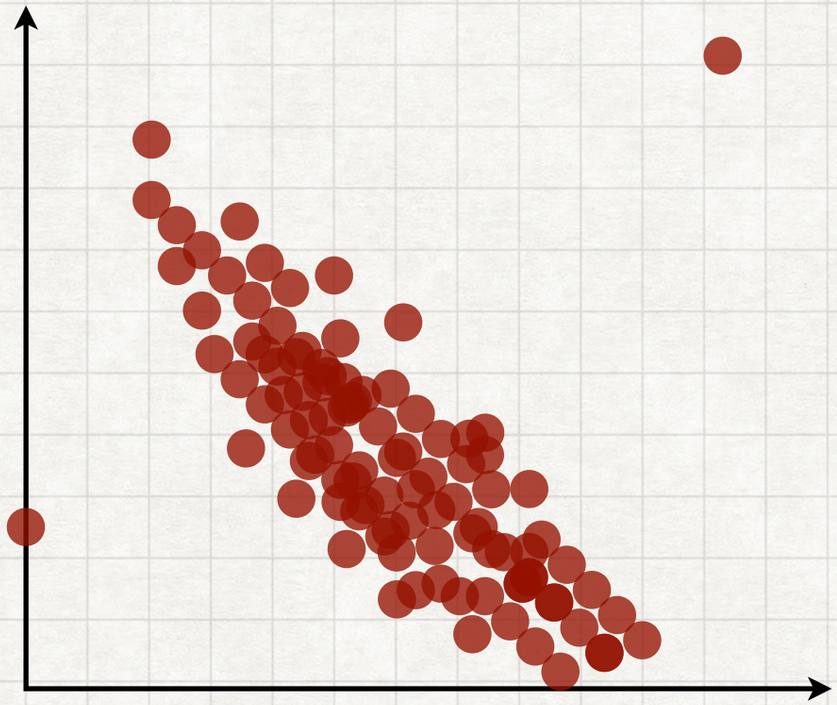
Histogram
Frequency vs. Log_{10} Price

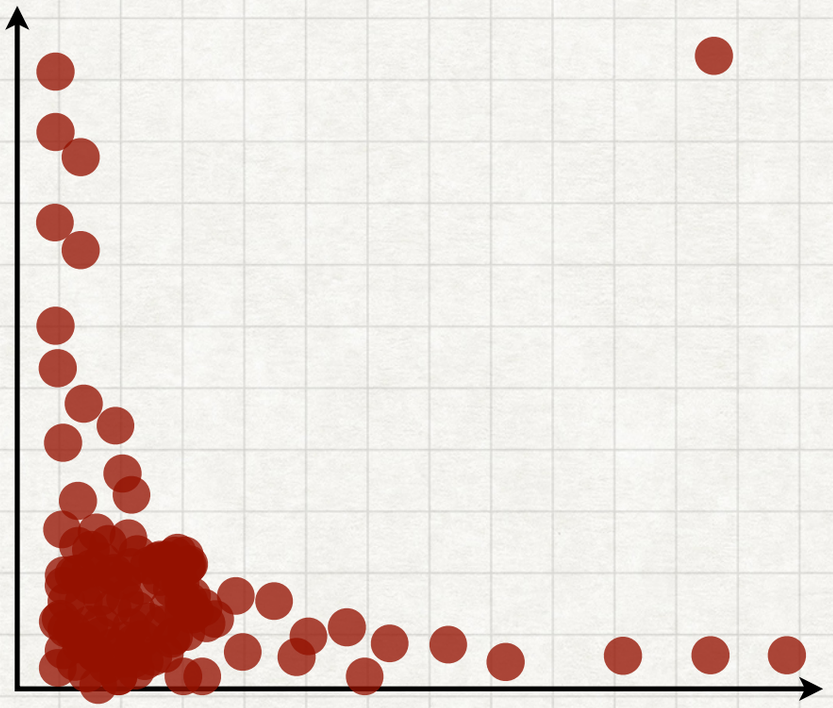


"Log-Log" Histogram
Log_{10} Freq vs. Log_{10} Price

WHAT ANOMALIES LOOK LIKE?

Outlying combinations of values



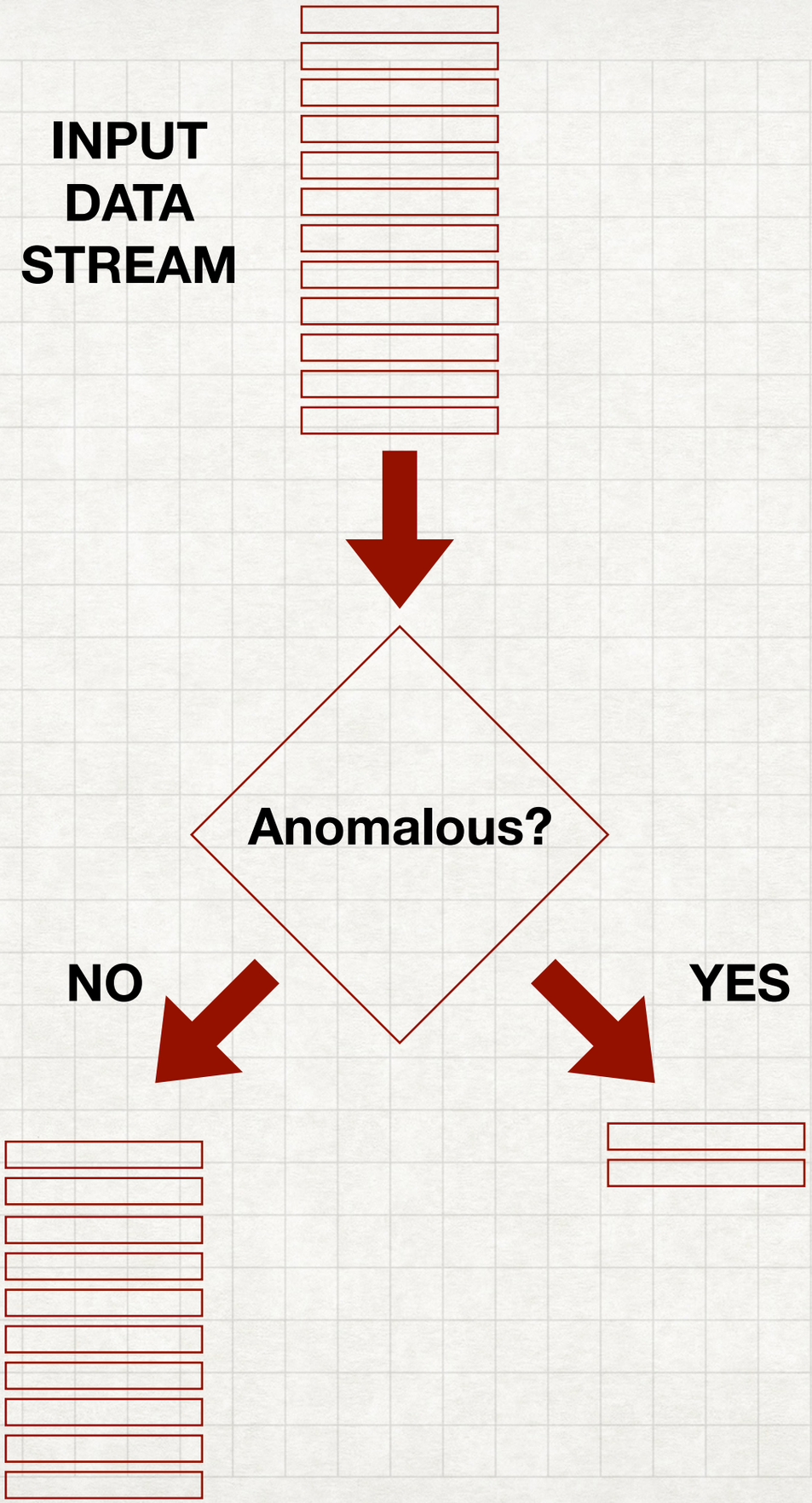


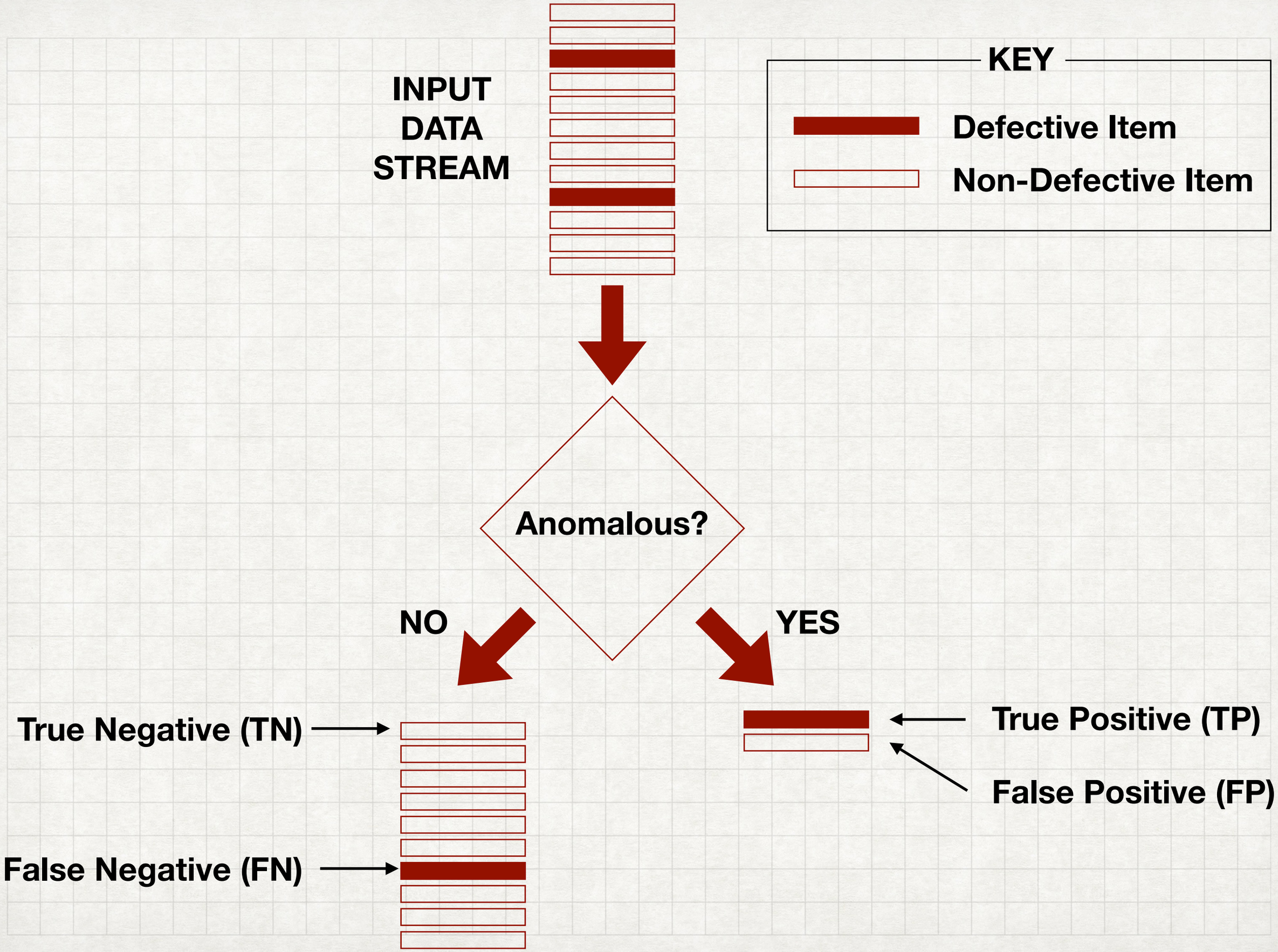
Again, may need log scales or similar to see in practice

AUTOMATED ANOMALY DETECTION

- Outlying values in one dimension/ variable
- Outlying combinations of values
- Patterns of regularity or irregularity in data streams
- Areas of high or low density
- Illegal data values
- Repetition

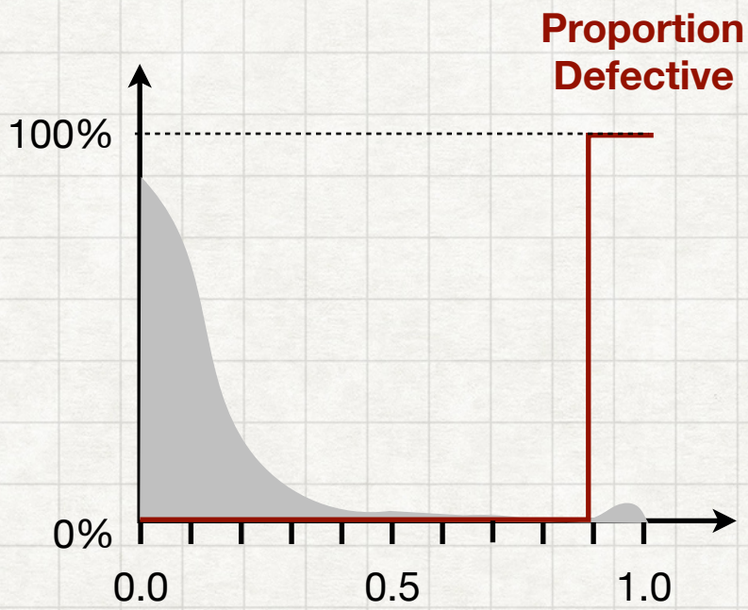
AUTOMATED ANOMALY DETECTION



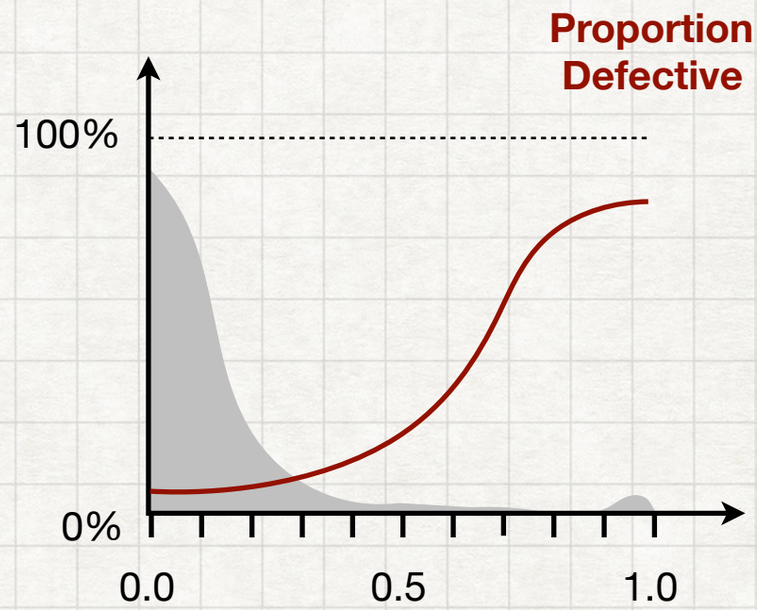

INPUT
DATA
STREAM
KEY
Defective Item
Non-Defective Item
Anomalous?
NO
YES
True Negative (TN)
False Negative (FN)
True Positive (TP)
False Positive (FP)

ANOMALY SCORES

Ideal Anomaly Score



Typical Anomaly Score



FALSE POSITIVE & FALSE NEGATIVE RATES

False Positive Rate — *Number of False Positives* — *Number of True* ***Negatives***

$$FPR = FP / (FP + TN)$$

the proportion of non-defective items that are flagged as anomalous

False Negative Rate — *Number of False Negatives* — *Number of True* ***Positives***

$$FNR = FN / (FN + TP)$$

the proportion of defective items that are flagged as non-anomalous

FALSE POSITIVE & FALSE NEGATIVE RATES

EXAMPLE

	detector flags as anomalous
10 000 items total	
1% defective	80%
99% non-defective	10%

$$FPR = FP / (FP + TN)$$

$$FNR = FN / (FN + TP)$$

TP	FN
FP	TN

EXERCISE: FILL IN ←

EXERCISE: Confirm formula gives FPR of 10% and FNR of 20%

EXERCISE: Calculate proportion of items flagged by the detector that are actually defective

FALSE POSITIVE & FALSE NEGATIVE RATES

EXAMPLE

10 000 items total

	detector flags as anomalous
1% defective	80%
99% non-defective	10%

$$FPR = FP / (FP + TN)$$

$$FNR = FN / (FN + TP)$$

TP	FN
80	20
FP	TN
990	8910

EXERCISE: FILL IN ←

EXERCISE: Confirm formula gives FPR of 10% and FNR of 20%

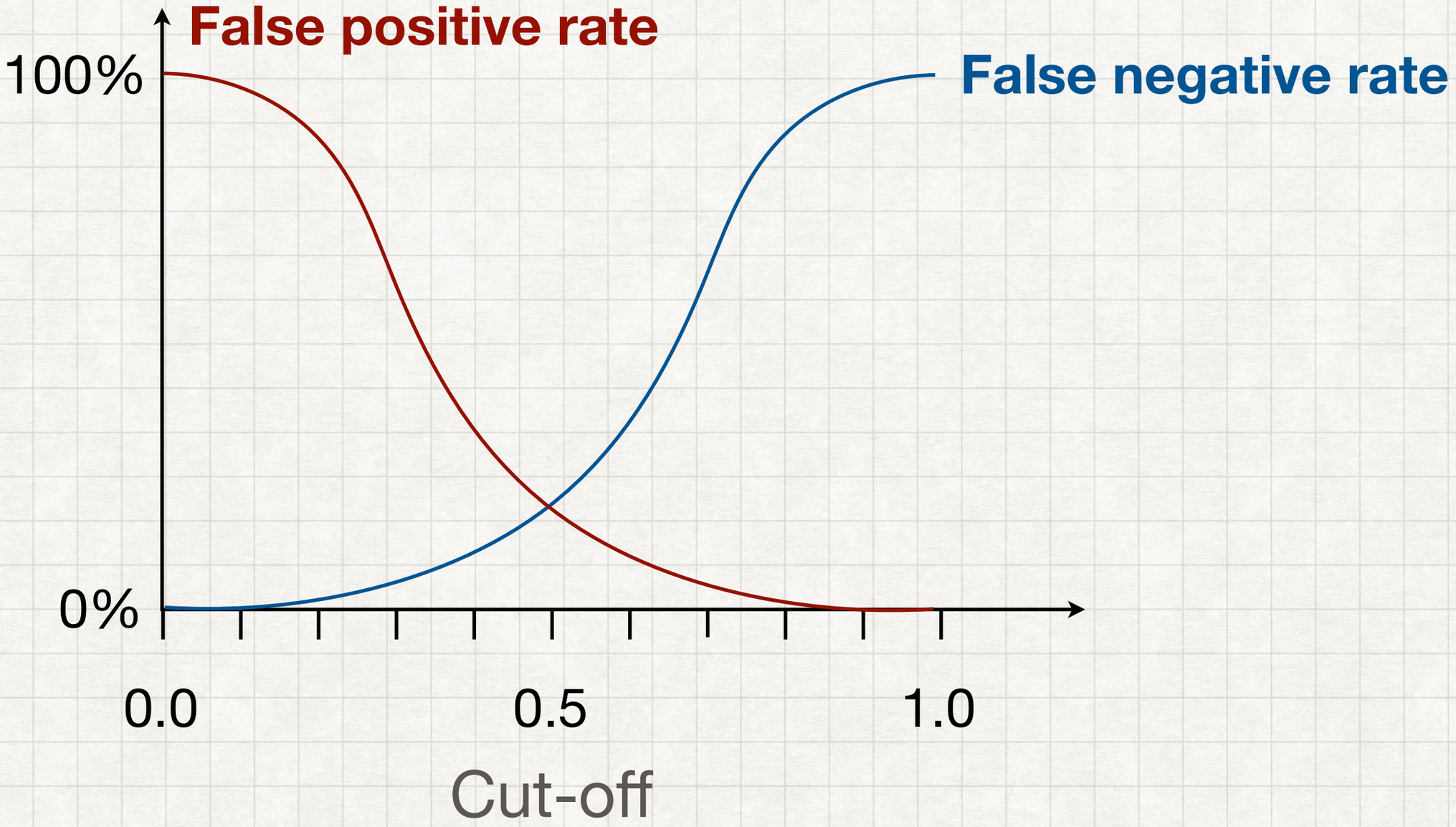
$$FPR = 990 / (990 + 8910) = 990 / 9900 = 10\%$$

$$FNR = 20 / (20 + 80) = 20 / 100 = 20\%$$

EXERCISE: Calculate proportion of items flagged by the detector that are actually defective

$$80 / (80 + 990) = 80 / 1070 \simeq 7.5\%$$

TRADE-OFF AS CUTOFF VARIES



Choosing cut-off depends on relative costs of true and false positives

PART II:
ONE-DIMENSIONAL ANOMALY DETECTION

EXAMPLE TRANSACTION STREAM

	id	category	price
0	710316821	QT	150.39
1	516025643	AA	346.69
2	414345845	QT	205.83
3	590179892	CB	55.61
4	117687080	QT	142.03
5	684803436	AA	152.10
6	611205703	QT	39.65
7	399848408	AA	455.67
8	289394404	AA	102.61
9	863476710	AA	297.82
10	534170200	KA	80.96
11	898969231	QT	81.39

CONSTRAINTS

- Field `id` (int): Identifier for item. Should not be null (`np.nan`), and should be unique in the table
- Field `category` (str): Should be one of “AA”, “CB”, “QT”, “KA” or “TB”
- Field `price` (float): unit price in pounds sterling. Should be non-negative and no more than 1,000.00.

FINDING NULLS

```
def find_nulls(df, col):
    okcol = col + '_nonnull_ok'
    df[okcol] = df[col].notna()
    null_rows = df[df[okcol] == False]
    if len(null_rows) > 0:
        print(null_rows[['id', 'category', 'price']])
    else:
        print('No nulls in column %s' % col)
    return null_rows


def find_all_nulls(df):
    for c in list(df):
        find_nulls(df, c)
```

FINDING DUPLICATES

```
def find_dup_ids(df):
    df['id_unique_ok'] = (df.groupby('id')['id']
                          .transform('count') == 1)

    dup_ids = df[df.id_unique_ok == False]['id']
    if len(dup_ids) > 0:
        cid = dup_ids.groupby(df.id).count()
        cid.rename(columns={'id':'count'})
        cid.reset_index()
        print(cid)
    return dup_ids
```

FINDING OUTLIERS

```
def find_bad_prices(df):
    df['price_ok'] = np.logical_and(
                            df['price'] >= 0,
                            df['price'] <= 1000.0)
    bad_prices = df[df.price_ok == False]
    if len(bad_prices) > 0:
        print(bad_prices[['id', ‘category',
                          'price']])
    return bad_prices
```

FINDING INVALID STRING VALUES

```
def find_bad_categories(df):
    allowed = ["AA", "CB", "QT", "KA", "TB"]
    df['category_ok'] = df['category'].isin(allowed)
    bad_cats = df[df.category_ok == False]
    if len(bad_cats) > 0:
        print(bad_cats[['id', 'category', 'price']])
    return bad_cats
```

FINDING ALL THE BADS

```
def find_bad_records(df):
    query = ('not (id_nonnull_ok '
                  'and id_unique_ok '
                  'and price_nonnull_ok '
                  'and price_ok '
                  'and category_nonnull_ok '
                  'and category_ok)')
    bads = df.query(query)
    print(bads)
    return bads
```

USING TDDA TO MAKE ALL THIS EASIER

TEST-DRIVEN DATA ANALYSIS

- Test-driven data analysis is methodology & software (open-source and commercial) for improving quality and robustness of analytical processes
- Two main components:
    - *Reference Testing:* extensions to **`unittest`** & **`pytest`** for testing analytical processes
    - *Automatic Constraint Discovery & Verification*.
- Can use the data verification capabilities as a general purpose anomaly detection framework, as we do here.
- We use the **`tdda`** library, available from PyPI.

EXAMPLE TRANSACTION STREAM

	id	category	price
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- Field **`id`** (int): Identifier for item. Should not be null (`np.nan`), and should be unique in the table
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- Field **`price`** (float): unit price in pounds sterling. Should be non-negative and no more than 1,000.00.

EXAMPLE TRANSACTION STREAM

```
{
  "fields": {
    "id": {
      "type": "int",
      "max_nulls": 0,
      "no_duplicates": true
    },
    "category": {
      "type": "string",
      "max_nulls": 0,
      "allowed_values":
        ["AA", "CB", "QT",
         "KA", "TB"]
    },
    "price": {
      "type": "real",
      "min": 0.0,
      "max": 1000.0,
      "max_nulls": 0
    }
  }
}
```

constraints.tdda

CONSTRAINTS

- Field **`id`** (int): Identifier for item. Should not be null (`np.nan`), and should be unique in the table
- Field **`category`** (str): Should be one of “AA”, “CB”, “QT”, “KA” or “TB”
- Field **`price`** (str): unit price in pounds sterling. Should be non-negative and no more than 1,000.00.

ANOMALY DETECTION WITH TDDA

COMMAND-LINE VERSION

(Assuming numpy and pandas already installed!)

```
pip install tdda
pip install feather-format
pip install pmmif
cd pydatalondon2018ad/oned

tdda detect data/items.feather \
            constraints.tdda   \
            bads.csv           \ location for output (.csv or .feather)
      --detect-per-constraint  \   write cols for each constraint
      --detect-output-fields       write all original cols too

cat bads.csv
```

CSV FILES IN TDDA LIBRARY

WE USE THESE OPTIONS FOR `pd.read_csv`

```
{
        'index_col': None,
        'infer_datetime_format': True,
        'quotechar': '"',
        'quoting': csv.QUOTE_MINIMAL,
        'escapechar': '\\',
        'na_values': ['', 'NaN', 'NULL'],
        'keep_default_na': False,
}
```

* *Pandas CSV reader does not readily allow empty strings and null values to co-exist when using blank for nulls.*

ANOMALY DETECTION WITH TDDA

API VERSION

```
from pmmif import featherpmm
from tdda.constraints import detect_df

path = 'data/items.feather'
df = featherpmm.read_dataframe(path).df

v = detect_df(df, ‘constraints.tdda',
              detect_per_constraint=True,
              detect_output_fields=[])
bads_df = v.detected()
print(bads_df)
```

GENERATING CONSTRAINT AUTOMATICALLY

COMMAND-LINE VERSION

```
tdda discover data/good_items.feather goods.tdda
```

or .csv file containing known good (non-anomalous) data

location for output constraints file

or

```
tdda discover data/good_items.feather goods.tdda \
      --rex
```

Also generate regular expressions characterizing string fields

GENERATED CONSTRAINTS FILE

```
{
    "fields": {
        "id": {
            "type": "int",
            "min": 100000546,
            "max": 899995057,
            "sign": "positive",
            "max_nulls": 0,
            "no_duplicates": true
        },
        ⋮
        "price": {
            "type": "real",
            "min": 0.0,
            "max": 985.18,
            "sign": "non-negative",
            "max_nulls": 0
        }
    }
}
```

```
"category": {
        "type": "string",
        "min_length": 2,
        "max_length": 2,
        "max_nulls": 0,
        "allowed_values": [
            "AA",
            "CB",
            "KA",
            "QT",
            "TB"
        ],
        "rex": [
            "^[A-Z]{2}$"
        ]
    },
```

from `--rex`

GENERATING CONSTRAINT AUTOMATICALLY

COMMAND-LINE VERSION

```
tdda discover data/good_items.feather goods.tdda
```

or .csv file containing known good (non-anomalous) data

location for output constraints file

or

```
tdda discover data/good_items.feather goods.tdda \
      --rex
```

Also generate regular expressions characterizing string fields

API CONSTRAINT GENERATION

```
from pmmif import featherpmm
from tdda.constraints import discover_df

path = 'data/good_items.feather'
df = featherpmm.read_dataframe(path).df

constraints = discover_df(df, inc_rex=True)
with open('autoconstraints.tdda', 'w') as f:
    f.write(constraints.to_json())
```