Data Preprocessing

Data Mining & Analytics INFO 254 / 154 - Spring '19

Prof. Zach Pardos

Preprocessing: Primer

Instance, rows, feature, attribute, column, target, label

	A	В	С	
1	Candidate	Interviewer	Rating	
2	Claudia S.	Manager A	4	
3	Oliver R.	Manager A	2	
4	Samuelson R.	Engineer A	5	
5	Alicia M.	Engineer B	1	
6	Oliver R.	Engineer B	5	
7	Claudia S.	Manager B	3	

Task: choose a candidate to hire

Data: 50 candidates each interviewed by two employees

Preprocessing: Primer

Instance, rows, feature, attribute, column, target, label

Raw input data

	А	В	С	Transformation		1
1	Candidate	Interviewer	Rating	Preprocessing /		
2	Claudia S.	Manager A	4	feature engineering	Classifier	
3	Oliver R.	Manager A	2			
4	Samuelson R.	Engineer A	5			
5	Alicia M.	Engineer B	1			
6	Oliver R.	Engineer B	5			
7	Claudia S.	Manager B	3			

Task: choose a candidate to hire

Data: 50 candidates each interviewed by two employees

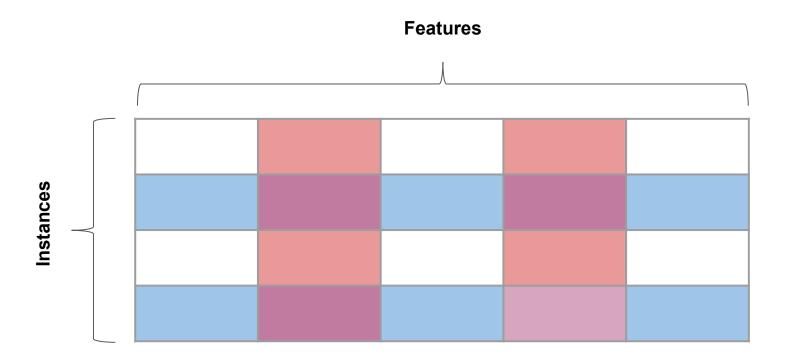
Preprocessing: Primer

Instance, rows, feature, attribute, column, target, label

Theoretical Primer

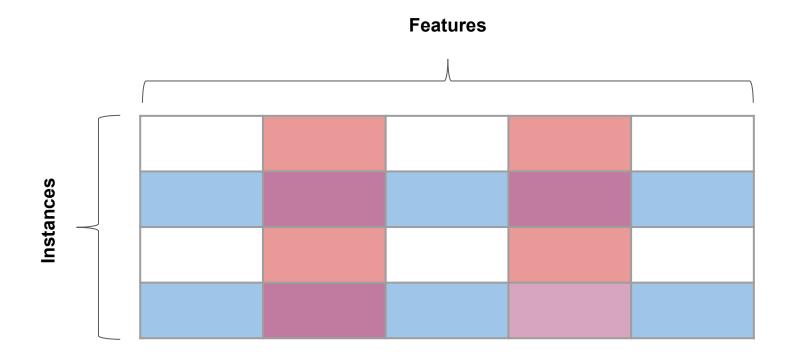
Data Preprocessing as a form of:

Summarization, Kernelization, Representation Learning



```
"votes": {
        "funny": 0,
        "useful": 2,
         "cool": 1
    },
"user_id": "Xqd0DzHaiyRqVH3WRG7hzg",
"" "15cdiuk7DmYqUAi6riGowg
    "review_id": "15SdjuK7DmYqUAj6rjGowg",
    "stars": 5,
    "date": "2007-05-17",
    "text": "dr. goldberg offers everything i look for in a general
practitioner. he's nice and easy to talk to without being patroni
zing; he's always on time in seeing his patients; he's affiliated with a top-notch hospital (nyu) which my parents have explained to m
e is very important in case something happens and you need surgery;
and you can get referrals to see specialists without having to see
him first. really, what more do you need? i'm sitting here tryin
g to think of any complaints i have about him, but i'm really drawi
ng a blank."
    "type": "review",
    "business_id": "vcNAWiLM4dR7D2nwwJ7nCA"
```

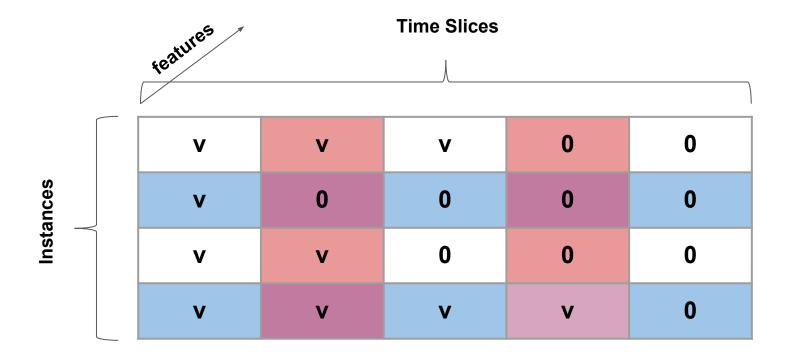
Instance, rows, feature, attribute, column, target, label



Most common form of representing data to a model

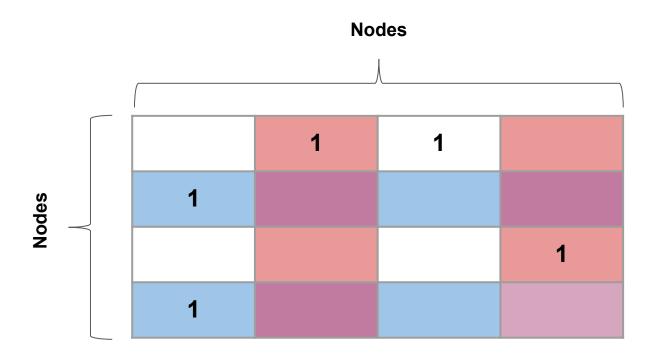
- Slight differences for: Time series, Networks

Instance, rows, feature, attribute, column, target, label

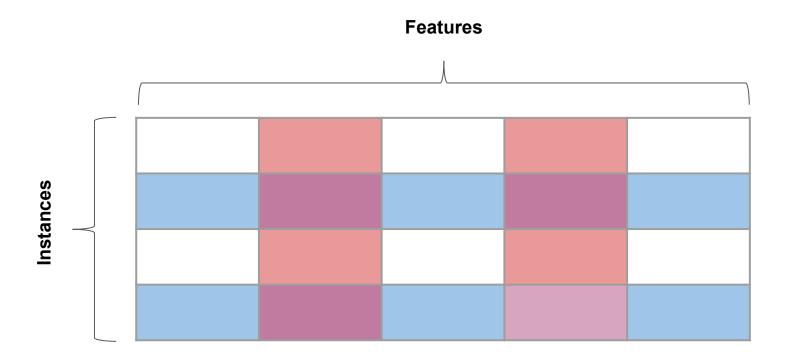


Time series

Instance, rows, feature, attribute, column, target, label

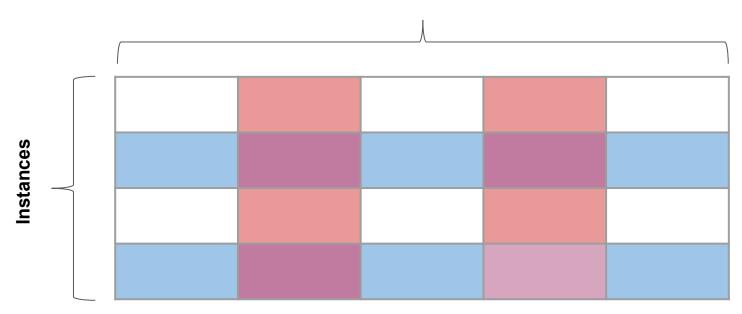


Networks (connections/relationships)



Instance, rows, feature, attribute, column, target, label

Features

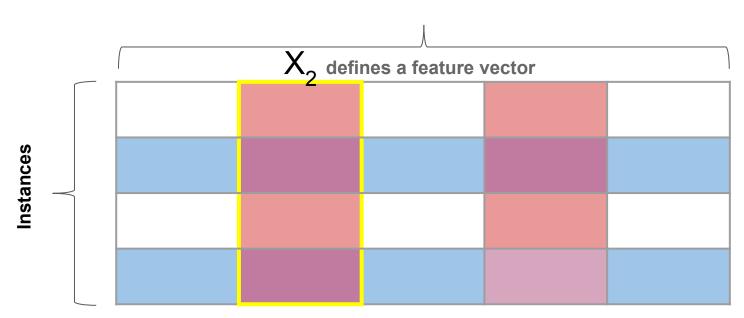


This dataset (matrix) can be expressed by:

features

<u>Instance, rows, feature, attribute, column, target,</u> label

Features

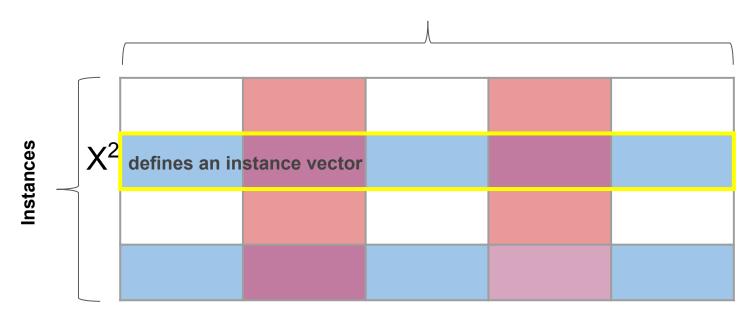


This dataset (matrix) can be expressed by:

features

<u>Instance, rows, feature, attribute, column, target,</u> label

Features

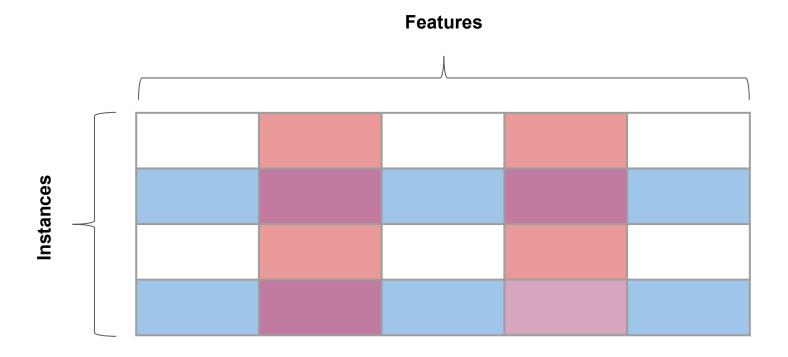


This dataset (matrix) can be expressed by:

X_m # of instances

features

Instance, rows, feature, attribute, column, target, label

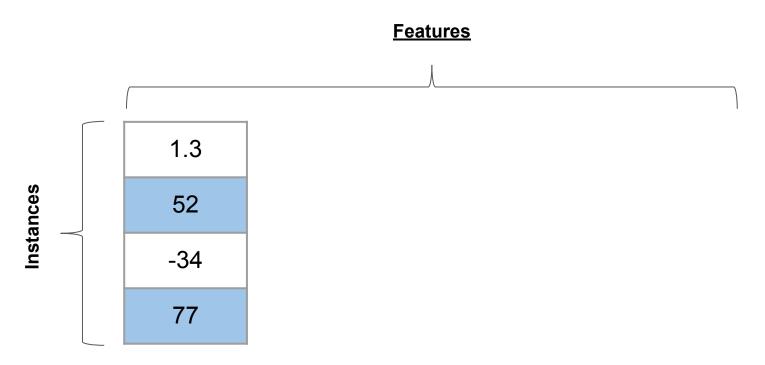


Where does the target coming from?

yelp_academic_dataset_review.json

```
"review id": "encrypted review id",
"user_id": "encrypted user id",
"business id": "encrypted business id",
"stars":star rating, rounded to half-stars,
"date": "date formatted like 2009-12-19",
"text": "review text",
"useful":number of useful votes received,
"funny":number of funny votes received,
"cool": number of cool review votes received,
"type": "review"
```

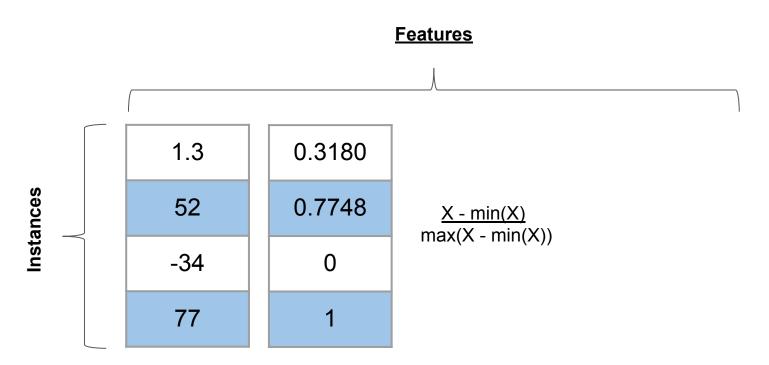
Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature?

How can it be represented to a classifier?

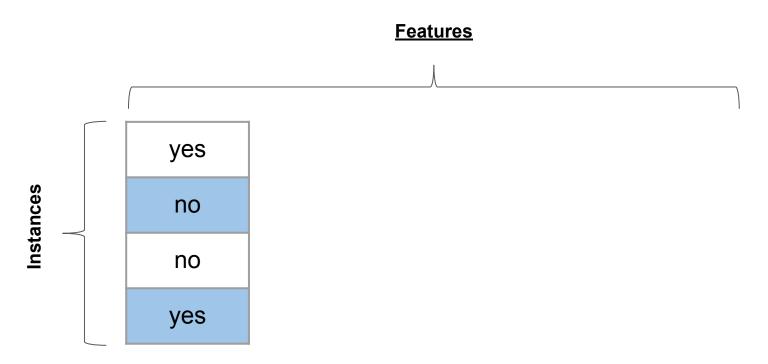
Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature? *Numeric*

How can it be represented to a classifier? As-is or normalized

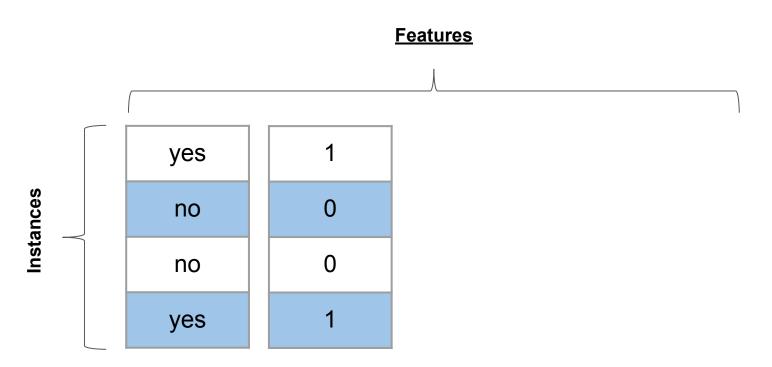
Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature?

How can it be represented to a classifier?

Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature? *Binary*

How can it be represented to a classifier? Os and 1s

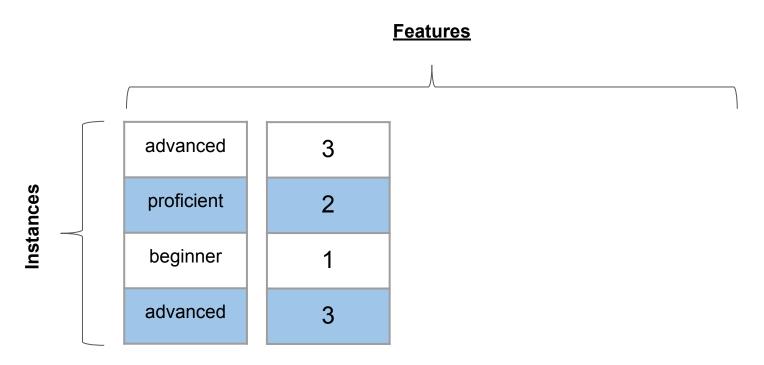
Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature?

How can it be represented to a classifier?

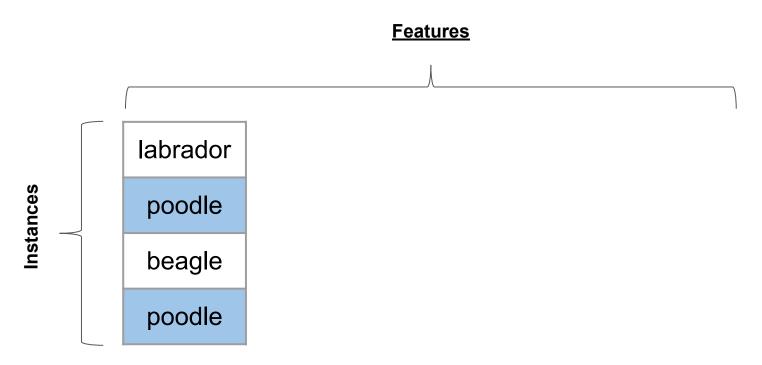
Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature? *Ordinal*

How can it be represented to a classifier? Ordered numeric

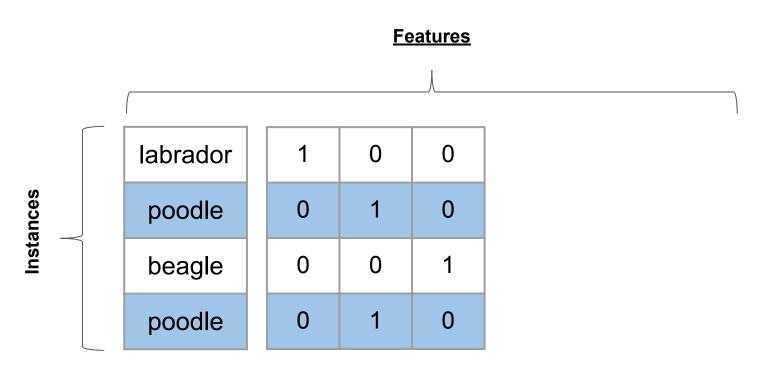
Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature?

How can it be represented to a classifier?

Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature? *Nominal*

How can it be represented to a classifier? One-hot

Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature?

How can it be represented to a classifier?

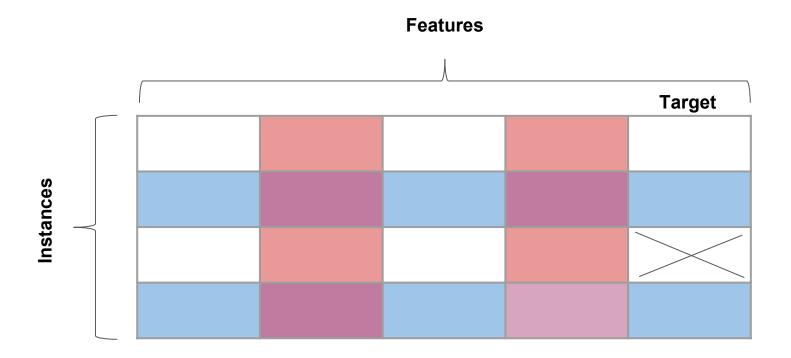
Feature types: 1. Binary 2. Numeric 3. Ordinal 4. Nominal



What is the type is this feature? *Nominal*

How can it be represented to a classifier? One-hot, numeric proxy

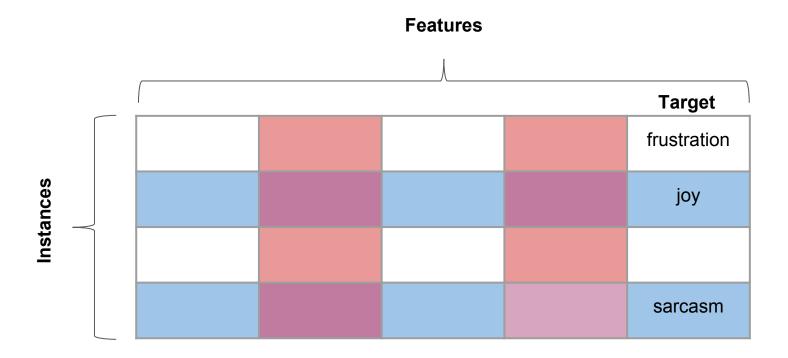
Instance, rows, feature, attribute, column, target, label



Where does the target coming from?

1) An existing feature that is missing from some instances

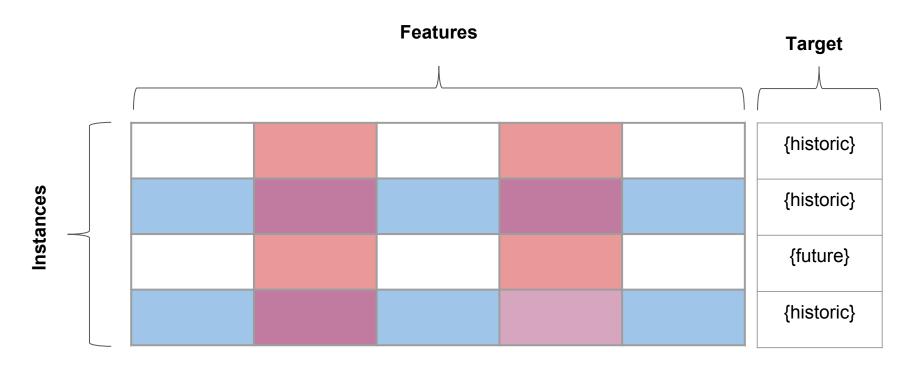
Instance, rows, feature, attribute, column, target, label



Where does the target coming from?

- 1) An existing feature that is missing from some instances
- 2) A hand labeled feature

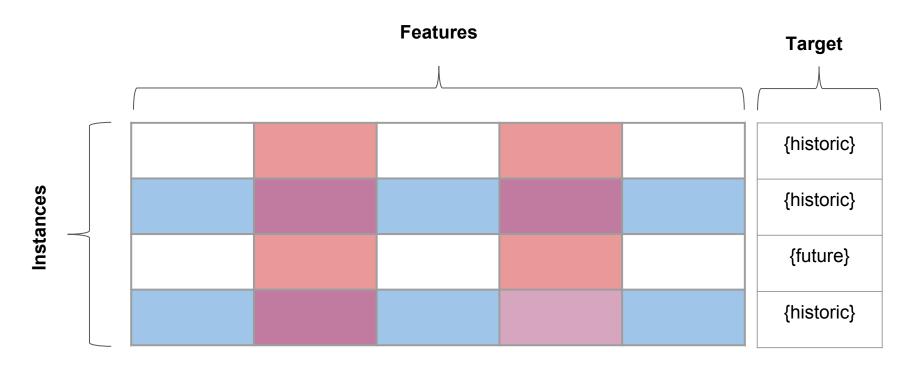
Instance, rows, feature, attribute, column, target, label



Where does the target coming from?

- 1) An existing feature that is missing from some instances
- 2) A hand labeled feature
- 3) A feature value that that will be known in the future

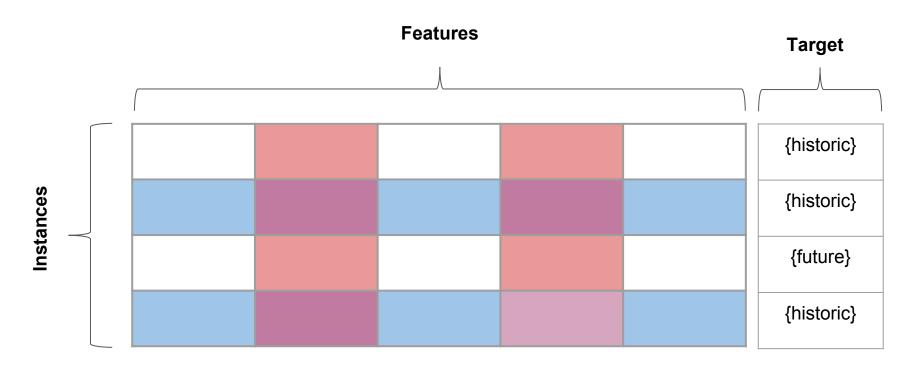
Instance, rows, feature, attribute, column, target, label



Classification: $X_m^n \longrightarrow Y^n$ (the target)

Rule of thumb: The greater the variation in X, the greater (and more challenging) the generalization being sought.

Instance, rows, feature, attribute, column, target, label



Classification: $X_m^n \longrightarrow Y^n$ (the target)

What is an Instance?

Weather Data:

Average daily temperature data for every US city for past 365 days

Date, City, Temperature

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1/26/2016, Berkeley, 56
1/25/2016, Berkeley, 54
```

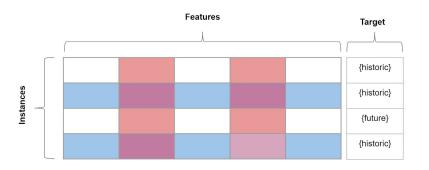
.

1/26/2016, Dallas, 67

1/25/2016, Dallas, 68

.

What is the target, features, and instances?



Weather Data:

A few potential representations to think about:

One representation could have the 365th day's temperature be the target and have 20 features which represent the historic temperatures from days 345 to 364.

This representation would be leaving out 344 days' worth of data (most of the dataset). To utilize more data, every contiguous 20 day period could be $X_{20}^{\#0}$ used as a feature set and the 21st day as the target.

Alternatively, if you wanted a single city centric dataset, the target could be the target at time T for, say, Berkeley and the features could be historic temperature data for all cities.

This is a region/location agnostic model. How can we add this information to the feature set?

School District Data:

Average middle school and high school class grades in an academic year for each student in a district for the past 5 years

AY, Student, Teacher, School, Grade Level, Avg. Grade

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2015-2016, Sammy Davis, Alabama High, 11, Hugh Laurie, B-2014-2015, Sammy Davis, Alabama High, 10, Jeremey Irons, C+
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.

2015-2015, Alex Rodriguez, Centennial, 7, Steve McQueen, A

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Book Text Data:

Average middle school and high school class grades in an academic year for each student in a district for the past 5 years

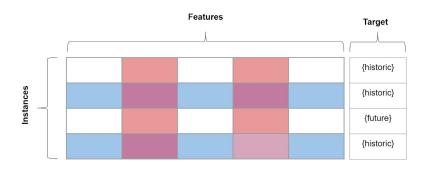
Book name, Complete text, Year of release, Current Amazon Sales Rank

A Brief History of Time, "Even if there is only..",. 1998, 1073

Data Mining: Concepts and Techniques (3rd), "Analyzing large..", 2011, 23899

.

What is the target, features, and instances?



Concluding thought:

Before getting into optimizing models

- Understand the problem you're trying to solve
- Does your representation of the input data make sense for solving the problem?

See you Thursday

- Thursday quiz will be 2-5 questions (from slides/reading)
- Tutorial followed by start of Lab

Questions?

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