Data Foundations: Exam Review

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Outline

Review

The Exam

Basic Coding Concepts

Machine Learning (Features and Evaluation)

Data Annotation

Feature Selection/Transformation and Missing Data

Missing Data

Review

Any Questions?

Review

The Exam

Basic Coding Concepts

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Exam

The Exam is available **NOW**. It is due next Tuesday!

- The exam has 20 questions
- There are two coding questions. They are slightly harder than Midterm 1. Come prepared
- There is one regex problem

  The rest of the questions focus on everything else covered that was taught after Exam 1
- The web scraping material is **NOT** on the exam.
- Most of the questions are multiple choice, some of the questions will be short answer, and there will be a few coding questions.
- Once you start the exam, you have **2 hours** to finish it.

Basic Coding Concepts and FileIO

- Basic data types and data structures (floats/ints, strings, lists, sets, dicts, ...)
- Conditional Statements (if, elif, else) and boolean expressions (and, not/!, in, or)
- Looping constructs (for, while), as well as how to use range().
- File IO (Text files, CSVs, XML, JSON, JSONL)

Object Oriented Programming

Object oriented programming is a way to arrange your code so that you can **zoom into 50 lines** of the code and **understand it** while **ignoring the other 999,950 lines** of code for the moment.

Methods vs Functions

A method is a **function** that is contained **within a class** and the objects that are constructed from the class.

An **object** contains both data and **methods** that manipulate that data.

- An object is active, not passive; it does things
- An object is responsible for its own data
  - But: it can expose that data to other objects

An object has state

An object contains both **data** and methods that manipulate that data

- The data represent the **state** of the object
- Data can also describe the relationships between this object and other objects
- Data is also known as “attributes”

Example: A “rabbit” object

Assume we want to create an object that represents a rabbit.

It would have **data**:

- How hungry it is
- How frightened it is
- Where it is

And **methods**:

- eat, hide, run, dig

Creating Objects in Python

example.py

```
class PartyAnimal:
    x = 0 # data/attribute
    def party(self): # Method
        self.x += 1
        print("So far", self.x)
```

Creating Objects in Python

example.py

```
class PartyAnimal:
        x = 0 # data/attribute
        def party(self): # Method
                self.x += 1
                print("So far", self.x) an = PartyAnimal()
an.party()
an.party()
an.party()
```

anthony@MacBook:~$ python example.py

```
So far 1
So far 2
So far 3
```

Object life-cycle

example.py

```
class PartyAnimal:
    x = 0
    def __init__(self): # Called when object is created/initialized
        print('I am constructed')
    def party(self):
        self.x = self.x + 1
        print('So far',self.x)
    def __del__(self): # Called when object is destroyed
        print('I am destructed', self.x)
an = PartyAnimal()
an.party()
an.party()
an = 42
print('an contains',an)
```

Object life-cycle

example.py

```
...
an = PartyAnimal()
an.party()
an.party()
an = 42
print('an contains',an)
```

anthony@MacBook:~$ python example.py

```
I am constructed
So far 1
So far 2
I am destructed 2
an contains 42
```

Inheritance

example.py

```
from party import PartyAnimal
class CricketFan(PartyAnimal):
        points = 0
        def six(self):
                self.points = self.points + 6
                self.party()
                print(self.name,"points",self.points)
s = PartyAnimal("Sally")
s.party()
j = CricketFan("Jim")
j.party()
j.six()
```

Inheritance

example.py

```
s = PartyAnimal("Sally")
s.party()
j = CricketFan("Jim")
j.party()
j.six()
```

anthony@MacBook:~$ python example.py

```
Sally constructed
Sally party count 1
Jim constructed
Jim party count 1
Jim party count 2
Jim points 6
```

Machine Learning

Main Topics:

- Data Annotation
- Feature Engineering
- Model Selection and Evaluation

Data Objects and Attribute Types

A **data object** represents an entity. Examples include...

- Customers
- Students/Professors/Courses
- Tweets
- Images
- Genes, Drugs, Procedures

A **attribute** is a data field (synonyms dimension/feature/variable)

Types of Attributes

`https://www.youtube.com/watch?v=N9fDIAflCMY`

- **Nominal** - hair_color (black, blonde, red, green?), martial_status (single married, divorced, widowed,...), occupation (teacher, dentist, programmer,...)
- **Binary (Boolean)** - smoker (yes or no), medical tests (positive or negative)
- **Ordinal** - drink_size (short, tall, grande, venti), grade (A, B, C, D, F), professional_rank (assistant, associate, full)
- **Numeric** - temperature (70°F), speed (400 mph)

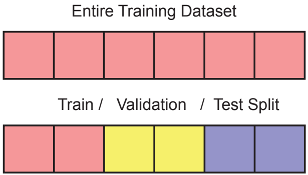
Model Evaluation

Model Selection: estimate the performance of different models in order to choose the best one.

Model Assessment: having chosen a final model, estimate its prediction error on new data.

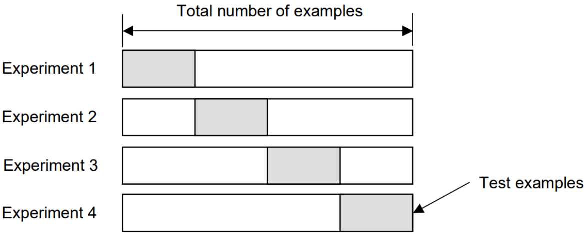
Model Selection Assessment

- Three-way data splits
  - **Training set**: A set of examples for learning
  - **Validation Set**: A set of examples used to tune the parameters/model selection
  - **Test set**: A set of examples **only** to assess the performance of the fully trained model.
    - After assessing the final model with the test set, **YOU MUST NOT** further tune your model.



K-Fold Cross-Validation

- Create K-fold partition of the dataset
  - For each of the K experiments, use K-1 folds for training and the remaining one for testing.



- The final error (evaluation measure) can be estimated as

$$E = \frac{1}{K} \sum_{i=1}^{K} E_i$$

How many folds are needed?

- With a large number of folds
  - $+$ The bias of true error rate is small
  - - Variance of true error rate will be large
  - - Large computational time (many experiments)
- With a small number of folds
  - $+$ Computation time reduced
  - $+$ Variance of estimator will be small
  - - The bias of estimator will be large (Conservative or higher than true error rate)
- In practice, the choice of the number of folds depends on the size of the dataset
  - For large datasets, 3-fold CV will be quite accurate
  - For very small datasets, we may have to use leave-one-out in order to train on as many examples as possible
- A common choice for K-Fold CV is K=10

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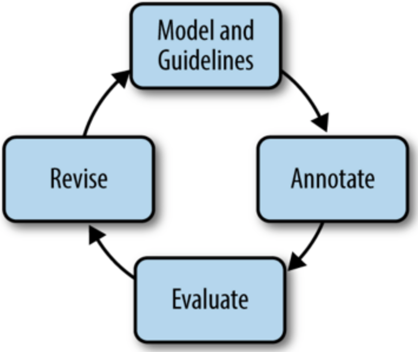
Annotation Pipeline



Pustejovsky and Stubbs (2012), Natural Language Annotation for Machine Learning

Annotation Process

1. Determine what to annotate.
2. Formalize the instructions for the annotation task
3. Perform a pilot annotation
4. Annotate the data
5. Compute and report inter-annotator agreement, and release the data.

Annotation Guidelines

Our goal: Given the constraints of our problem, how can we formalize our descriptions of the annotation process **to encourage multiple annotators to provide the same judgment?**

Annotation Guidelines

- What is the goal of the project?
- What is each class called and how is it used? (Be specific: provide examples and discuss gray areas)
- What **exactly** should be annotated and what should be left alone?

Pustejovsky and Stubbs (2012), Natural Language Annotation for Machine Learning

Practicalities

- Annotation takes time/concentration (can't do it 8 hours a day)

- Annotators get better as they annotate (earlier annotations not as good as later ones)

Why not do it yourself?

- Expensive/time-consuming
- Multiple people provide a measure of consistency: is the task well enough defined?
- Low agreement = not enough training, guidelines not well enough defined, task is bad.

Adjudication

- Adjudication is the process of deciding on a single annotation for a piece of text, using information about the **independent annotations**.
- Can be **time-consuming** (or more so) as primary annotation.
- Does **NOT** need to be identical with the primary annotation. (both annotators can be wrong by chance)

Fleiss' kappa

- Same fundamental idea of measuring the observed agreement compared to the agreement we would expect by chance.

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

- With N $>$ 2, we calculate agreement among **pairs** of annotators.

Fleiss' Kappa

n_{ij} is the number of annotators that agree on assigning the i-th class to the j-th item.

o is the total number of annotators

K is the number of classes

For item i with n annotations, how many annotators agree, among all n(n-1) possible pairs.

$$P_i = \frac{1}{o(o-1)} \sum_{j=1}^{K} n_{ij}(n_{ij} - 1)$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	**0.4**
Tweet 2	9	1	0	
Tweet 3	3	5	2	
Tweet 4	2	0	8	
p_j				[redacted]

$$P_1 = \frac{1}{10(10-1)} * (3*2 + 1*0 + 6*5) = \mathbf{0.4}$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	**0.6444**
p_j				[redacted]

$$P_4 = \frac{1}{10(10-1)} * (2 * 1 + 0 * -1 + 8 * 7) = \mathbf{0.6444}$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	0.6444
p_j				[redacted]

N is the total number of items (Total Tweets in this example)

Average observed agreement among all items

$$P_o = \frac{1}{N}\sum_{i=1}^{N} P_i = \frac{1}{4} * (0.4 + 0.8 + 0.3111 + 0.6444) = 0.5388$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	0.6444
p_j	**0.425**			[redacted]

N is the total number of items (Total Tweets in this example)
o is the total number of annotators
Probability of category j

$$p_j = \frac{1}{N * o} \sum_{i=1}^{N} n_{ij}$$

$$p_{positive} = \frac{1}{4 * 10} * (3 + 9 + 3 + 2) = \mathbf{0.425}$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	0.6444
p_j	0.425	0.175	**0.4**	[redacted]

N is the total number of items (Total Tweets in this example)
o is the total number of annotators
Probability of category j

$$p_j = \frac{1}{N * o} \sum_{i=1}^{N} n_{ij}$$

$$p_{neutral} = \frac{1}{4 * 10} * (6 + 0 + 2 + 8) = \mathbf{0.4}$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	0.6444
p_j	0.425	0.175	0.4	[redacted]

Expected agreement by chance – joint probability two raters pick the same label is the product of their independent probabilities of picking that label
K is the number of classes

$$P_e = \sum_{j=1}^{K} p_j * p_j = 0.425 * 0.425 + 0.175 * 0.175 + 0.4 * 0.4 = \mathbf{0.3715}$$

Fleiss' kappa

- Same fundamental idea of measuring the observed agreement compared to the agreement we would expect by chance.

$$\kappa = \frac{P_o - P_e}{1 - P_e} = \frac{0.5388 - 0.3715}{1 - 0.3715} = \mathbf{0.2662}$$

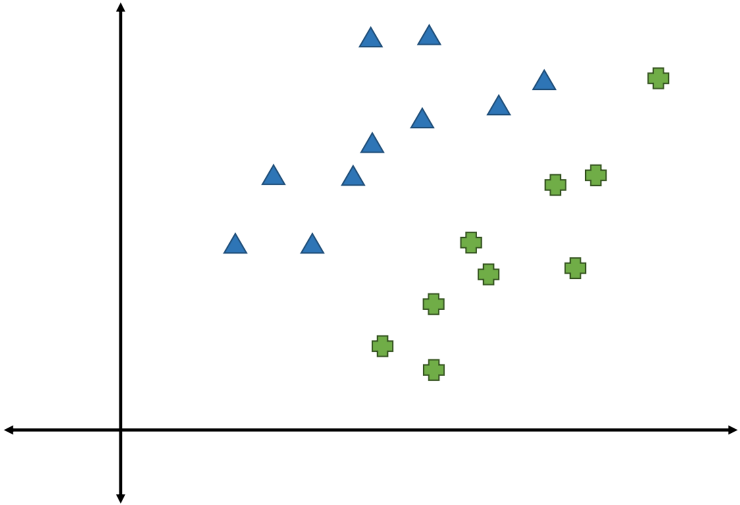
Fleiss' Kappa

"Good" values are subject to interpretation, but rule of thumb

Score Range	Interpretation
0.81 - 1.00	Almost Perfect
0.61 - 0.80	Substantial agreement
0.41 - 0.60	Moderate agreement
0.21 - 0.40	Fair agreement
0.01 - 0.20	Slight agreement
< 0.0	Poor agreement

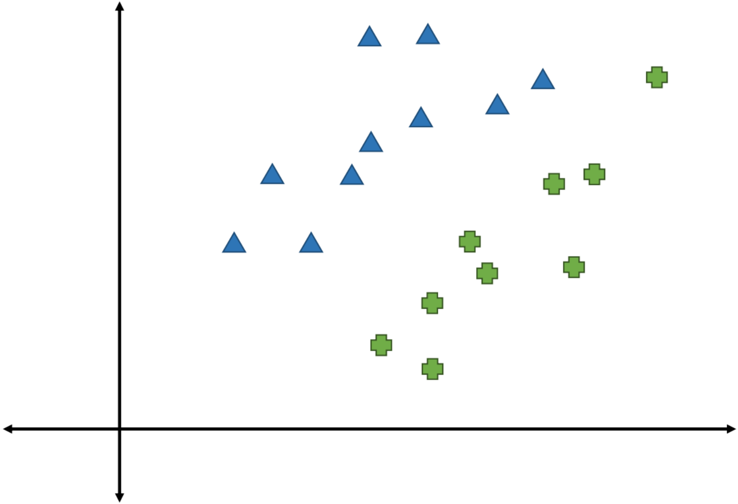
Geometric Intuition of Feature Selection and PCA

Suppose we have two dimensions (two features)



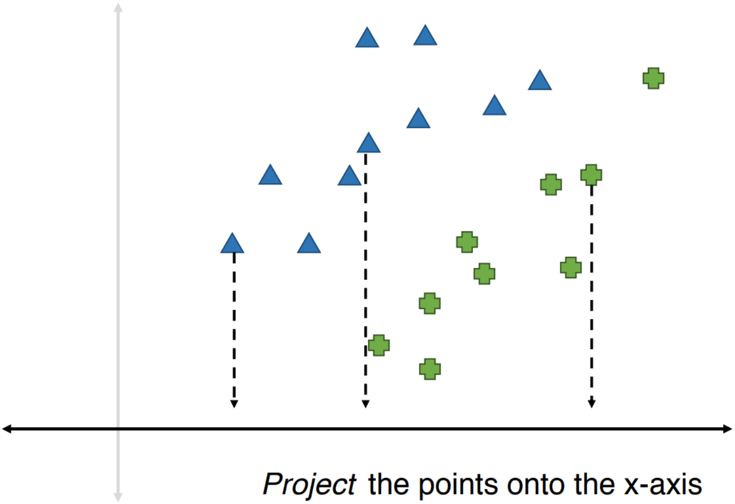
Geometric Intuition: Feature Selection

Feature selection: choose one of the two features to keep



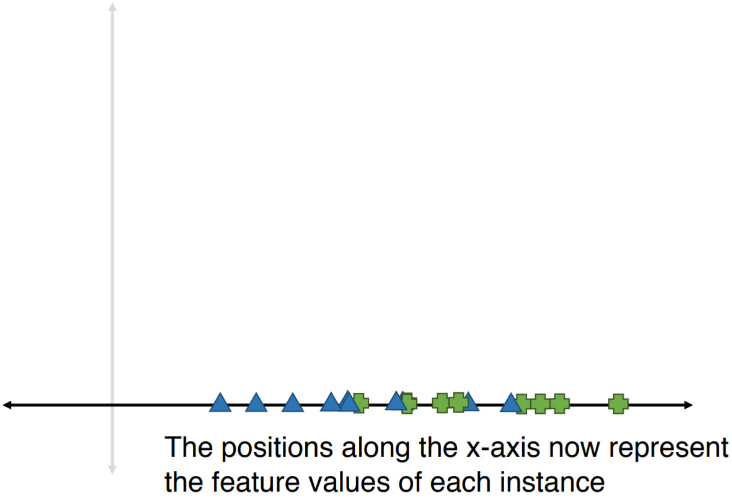
Geometric Intuition: Feature Selection

Suppose we choose the feature represented by the x-axis



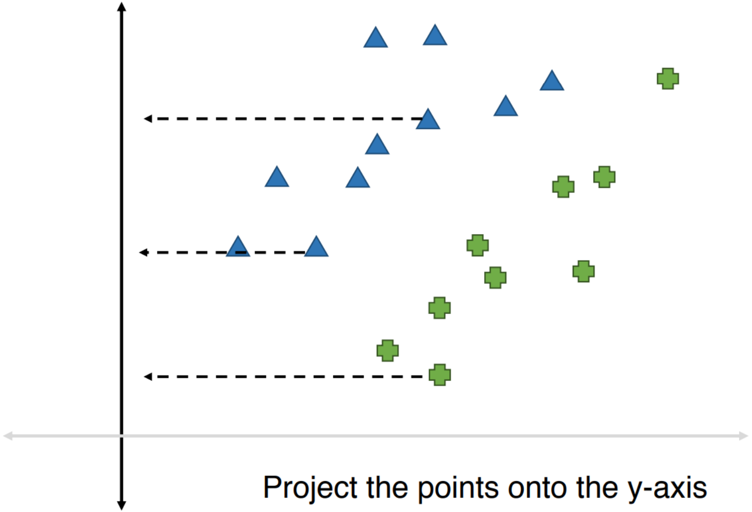
Geometric Intuition: Feature Selection

Suppose we chose the feature represented by the x-axis



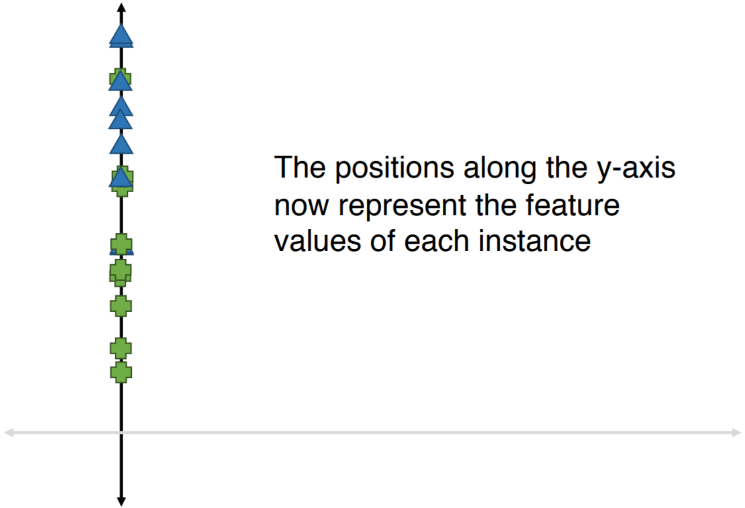
Geometric Intuition: Feature Selection

Suppose we choose the feature represented by the y-axis



Geometric Intuition: Feature Selection

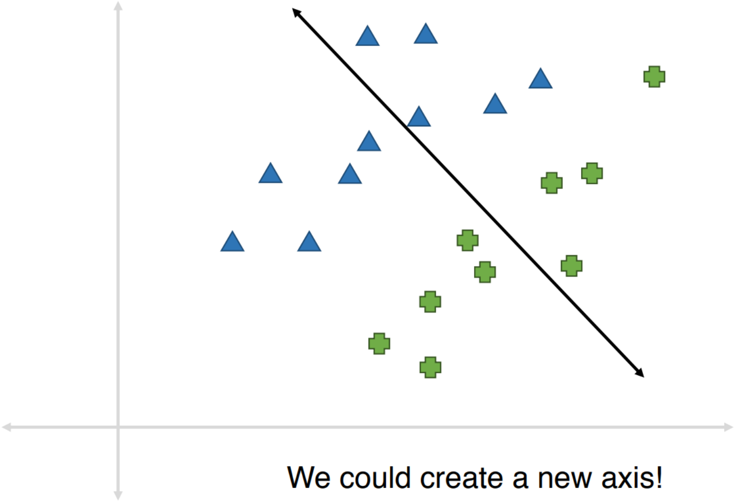
Suppose we choose the feature represented by the y-axis



The positions along the y-axis now represent the feature values of each instance

Geometric Intuition: Feature Transformation

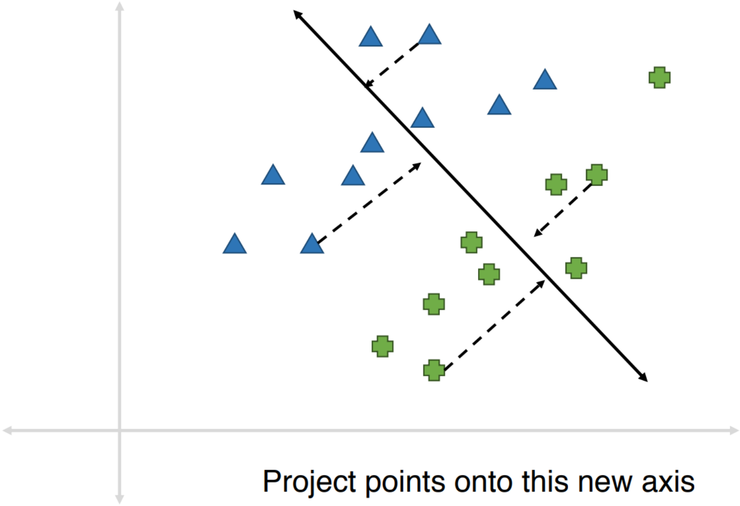
We don't have to restrict ourselves to picking either the x-axis or the y-axis



We could create a new axis!

Geometric Intuition: Feature Transformation

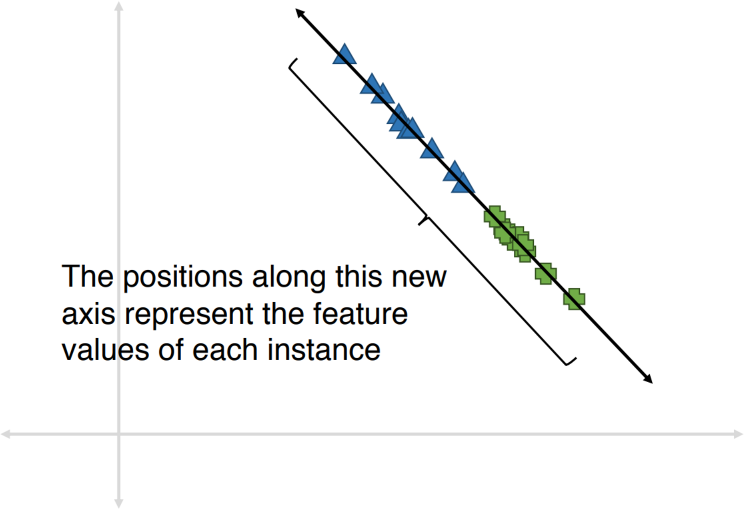
We don't have to restrict ourselves to picking either the x-axis or the y-axis



Project points onto this new axis

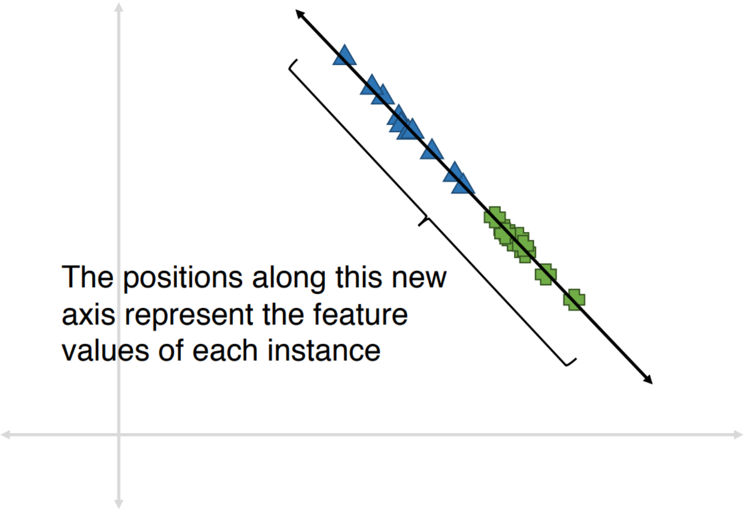
Geometric Intuition: Feature Transformation

We don't have to restrict ourselves to picking either the x-axis or the y-axis



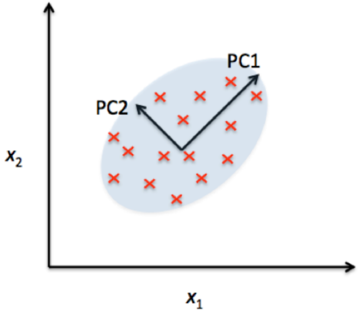
Geometric Intuition: Feature Transformation

This is an example of **transforming** the feature space (as opposed to **selecting** a subset of features)



Principle Component Analysis

Principle component analysis (**PCA**) is a widely used technique that chooses new axes to project the data onto



The new axes are called the **principle components**

Principle Component Analysis

PCA does not use any information about the class labels

- **Unsupervised** dimensionality reduction
- This has advantages and disadvantages

So, how does PCA decide how to choose axes?

- Basic idea: pick an axis so that the values will have **high variance** once projected onto it

Types of Missing Data

- Missing Completely at Random (MCAR)
  - P(missing) is unrelated to the process under study
- Missing at Random (MAR)
  - P(missing) depends only on **observed data**
- Missing Not at Random (MNAR)
  - P(missing) depends on both observed and **unobserved data**.

Type type of missing data drastically affects what we can ultimately do to compensate for missing-ness

Complete Case Analysis

Delete all rows with **any missing values** at all, so you are left only with observations where all variables are observed.

This is the **easiest way to handle missing data**. In some cases it will work fine; **in others, ????**

- Loss of sample will lead to variance larger than reflected by the size of your data

- May bias your sample

Missing Value Skipping: Pros and Cons

Pros

- Easy to understand and implement
- Can be applied to any model (decision trees, logistic regression, linear regression, ...)

Cons

- Removing data points and features may remove important information from the data
- Unclear when it's better to remove data points versus features
- Doesn't help if data is missing at test time

Mode

Credit	Term	Income	y
Excellent	3 yrs	High	safe
Fair	?	Low	Risky
Fair	3 yrs	High	Safe
Poor	5 yrs	High	Risky
Excellent	3 yrs	Low	Risky
Fair	5 yrs	High	Safe
Poor	3 yrs	Low	Risky
Poor	?	Low	Safe
Fair	?	High	Safe

Credit	Term	Income	y
Excellent	3 yrs	High	safe
Fair	3 yrs	Low	Risky
Fair	3 yrs	High	Safe
Poor	5 yrs	High	Risky
Excellent	3 yrs	Low	Risky
Fair	5 yrs	High	Safe
Poor	3 yrs	Low	Risky
Poor	3 yrs	Low	Safe
Fair	3 yrs	High	Safe

Impute each feature with missing values:

- **Categorical features use mode**: Most popular value (mode) of non-missing x_i
- **Numerical features use average or median**: Average or median value of non-missing x_i

There are other methods, e.g., expectation-maximization algorithm, regressing/classifying on missing columns

Missing Value Imputation: Pros and Cons

Pros

- Easy to understand and implement
- Can be applied to any model (decision trees, logistic regression, linear regression, ...)
- Can be used at prediction time using the same imputation rules

Cons

- May result in systematic errors
  - Example: Feature "age" missing in all banks in Washington by state law

The End

Good Luck! Email me if you have any questions or concerns.