Introduction to Pattern Recognition

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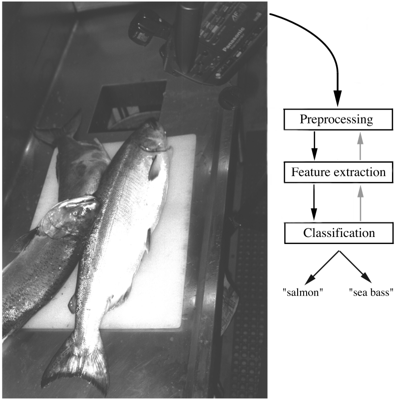
Example: Sorting Fish

Salmon

Sea Bass

Example: Sorting Fish
Pattern Recognition System Requirements

- Set up a camera to watch the fish coming through on the conveyor belt.
- Classify each fish as salmon or sea bass.
- Prefer to mistake sea bass for salmon.

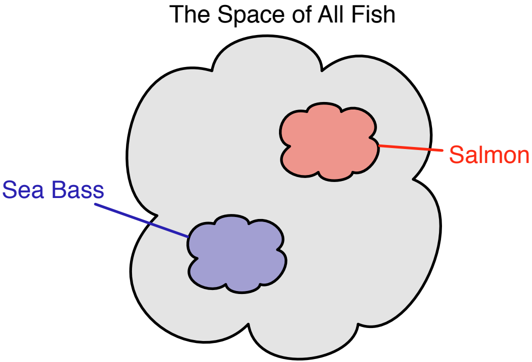


A Note On Preprocessing

- Inevitably, preprocessing will be necessary.
- *Preprocessing* is the act of modifying the input data to simplify subsequent operations without losing relevant information.
- Examples of preprocessing (for varying types of data):
  - Noise removal.
  - Element segmentation;
    - Spatial.
    - Temporal.
  - Alignment or registration of the query to a canonical frame.
  - Fixed transformation of the data:
    - Change color space (image specific).
    - Wavelet decomposition.
  - Transformation from denumerable representation (e.g., text) to a 1-of-B vector space.
- **Preprocessing** is a key part of our Pattern Recognition toolbox, but we will talk about it directly very little in this course.

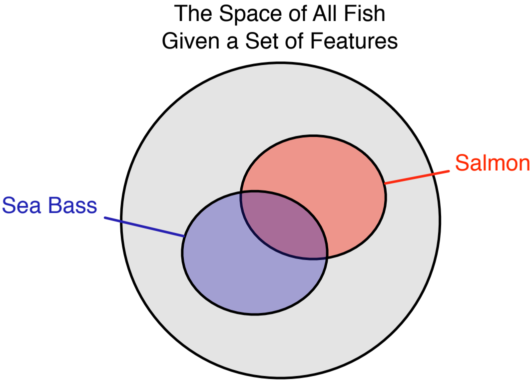
Patterns and Models

Ideal State Space



- Clear that the populations of salmon and sea bass are indeed distinct.
- The *space of all fish* is quite large. Each dimension is defined by some property of the fish, most of which we cannot even measure with the camera.

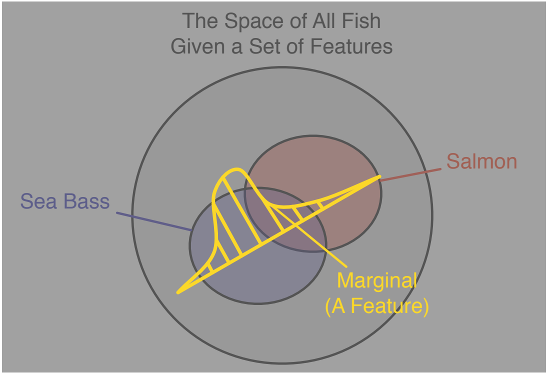
Patterns and Models
Real State Space



- When we choose a set of possible features, we are projecting this very high dimension space down into a lower dimension space.

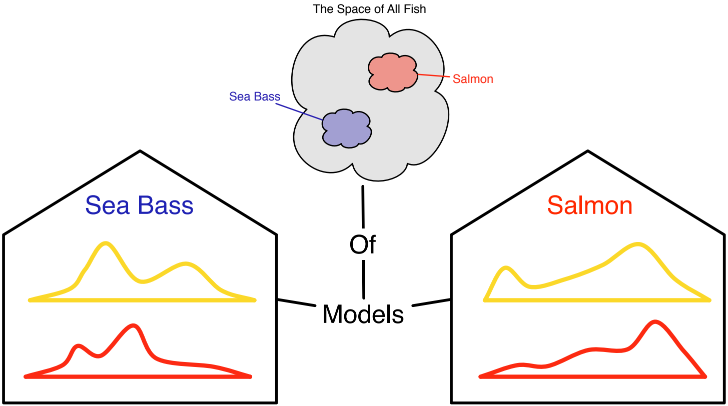
Patterns and Models

Features as Marginals



- And indeed, we can think of each individual feature as a single marginal distribution over the space.
- In other words, a projection down into a single dimension space.

Patterns and Models
Models

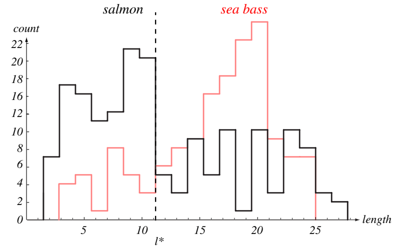


- We build a model of each phenomenon we want to classify, which is an approximate representation given the features we've selected.

Selecting Feature(s) for the Fish

- Suppose an expert at the fish packing plant tells us that length is *the best* feature.
- We **cautiously trust** this expert. Gather a few examples from our installation to analyze the length feature.
  - These examples are our **training set**.
  - Want to be sure to gather a representative population of them.
  - We analyze the length feature by building histograms: **marginal distributions**.

Histogram of the Length Feature



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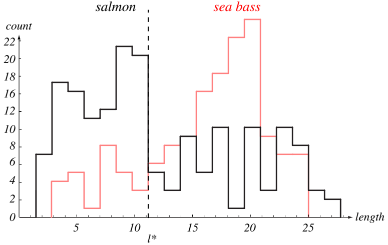
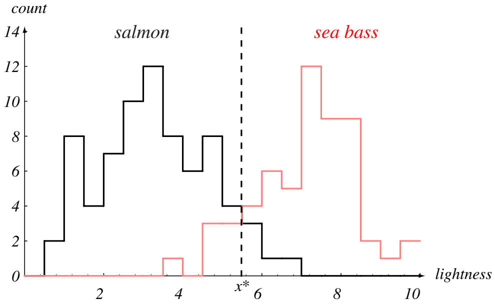


- But this is a disappointing result. The sea bass length does exceed the salmon length on average, but clearly not always.

Selecting Feature(s) for the Fish
Lightness Feature

- Try another feature after inspecting the data: **lightness**.

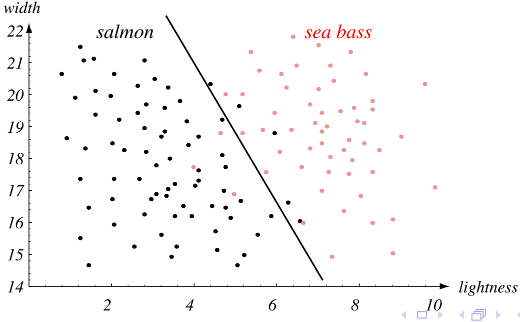


- This feature exhibits a much better separation between the two classes.

Feature Combination

- Seldom will one feature be enough in practice.
- In the fish example, perhaps lightness, x_1, and width, x_2, will jointly do better than any alone.
- This is an example of a 2D feature space:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad . \tag{1}$$



Curse Of Dimensionality

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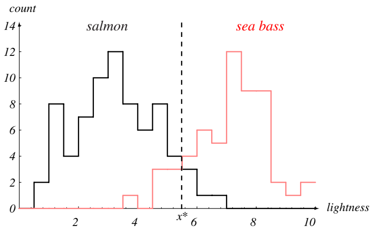
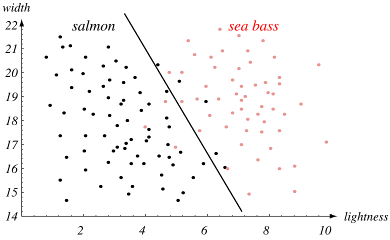
  - How do we know beforehand which features will work best?
  - What happens when there is feature redundance/correlation?

Decision Boundary

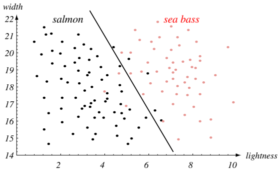
- The **decision boundary** is the sub-space in which classification among multiple possible outcomes is equal. Off the decision boundary, all classification is unambiguous.

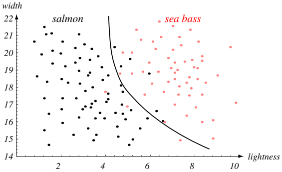


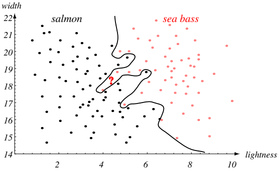


Bias-Variance Dilemma

- Depending on the available features, complexity of the problem and classifier, the decision boundaries will also vary in complexity.







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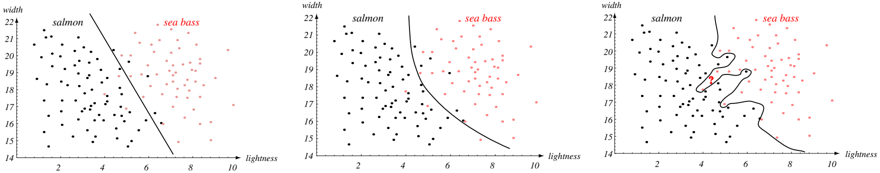

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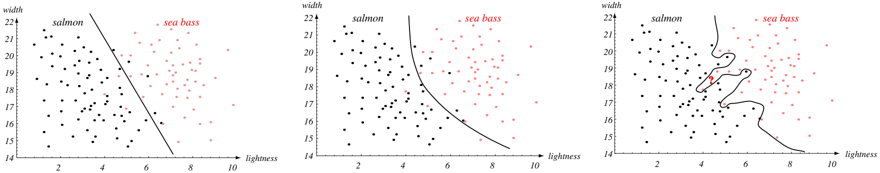

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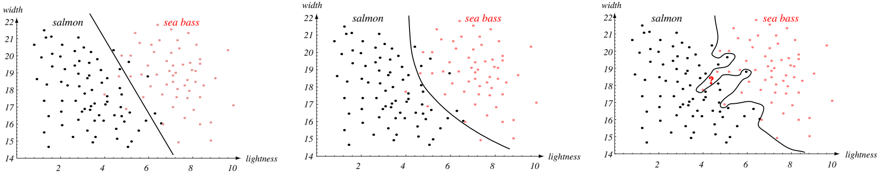
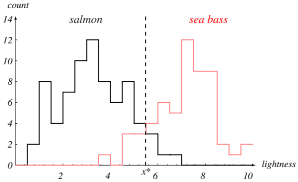


- Simple decision boundaries (e.g., linear) seem to miss some obvious trends in the data — **variance**.
- Complex decision boundaries seem to lock onto the idiosyncracies of the training data set — **bias**.
- A central issue in pattern recognition is to build classifiers that can work properly on novel query data. Hence, **generalization** is key.
- Can we predict how well our classifier will generalize to novel data?

Decision Theory

- In many situations, the consequences of our classifications are not equally costly.
- Recalling the fish example, it is acceptable to have tasty pieces of salmon in cans labeled sea bass. But, the converse is not so.
- Hence, we need to adjust our decisions (decision boundaries) to incorporate these varying costs.
- For the lightness feature on the fish, we would want to move the boundary to smaller values of lightness.



- Our underlying goal is to establish a decision boundary to minimize the overall cost; this is called **decision theory**.

Pattern Recognition

- Any ideas?

Pattern Recognition

- DHS: Pattern recognition is the act of taking in raw data and taking an action based on the "category" of the pattern.
- DHS: Pattern classification is to take in raw data, eliminate noise, and process it to select the most likely model that it represents.
- Jordan: The field of pattern recognition is concerned with the automatic discovery of regularities in data through the use of computer algorithms and with the use of these regularities to take actions such as classifying data into different categories.

Types of Pattern Recognition Approaches

- Statistical
  - Focus on statistics of the patterns.
  - The primary emphasis of our course.
- Syntactic
  - Classifiers are defined using a set of logical rules.
  - Grammars can group rules.

Feature Extraction and Classification

- **Feature Extraction** — to characterize an object to be recognized by measurements whose values are very similar for objects in the same category, and very different for objects in different categories.
  - Invariant features—those that are invariant to irrelevant transformations of the underlying data—are preferred.
- **Classification** — to assign an category to the object based on the feature vector provided during feature extraction.

Feature Extraction and Classification

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- **Classification** — to assign an category to the object based on the feature vector provided during feature extraction.
- The perfect feature extractor would yield a representation that is trivial to classify.
- The perfect classifier would yield a perfect model from an arbitrary set of features.
- But, these are seldom plausible.

Feature Extraction and Classification
Classification Objective Functions

- For classification, there are numerous underlying objective functions that we can seek to optimize.
- **Minimum-Error-Rate** classification seeks to minimize the the error rate: the percentage of new patterns assigned to the wrong category.
- **Total Expected Cost**, or **Risk** minimization is also often used.
- Important underlying questions are
  - How do we map knowledge about costs to best affect our classification decision?
  - Can we estimate the total risk and hence know if our classifier is acceptable even before we deploy it?
  - Can we bound the risk?

No Free Lunch Theorem

- A question you're probably asking is **What is the best classifier?**
- Any ideas?

No Free Lunch Theorem

- A question you're probably asking is **What is the best classifier?**
- Any ideas?
- We will learn that indeed no such generally **best** classifier exists.
- This is described in the **No Free Lunch Theorem**.
  - If the goal is to obtain good generalization performance, there are no context-independent or usage-independent reasons to favor one learning or classification method over another.
  - When confronting a new pattern recognition problem, appreciation of this thereom reminds us to focus on the aspects that matter most—prior information, data distribution, amount of training data, and cost or reward function.

Analysis By Synthesis

- The availability of large collections of data on which to base our pattern recognition models is important.
- In the case of little data (and sometimes even in the case of much data), we can use **analysis by synthesis** to test our models.
- Given a model, we can randomly sample examples from it to analyze how close they are to
  - our few examples and
  - what we expect to see based on our knowledge of the problem.

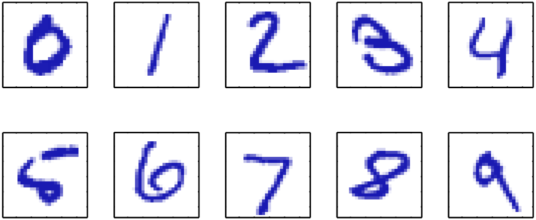
Classifier Ensembles

- Classifier combination is obvious – get the power of multiple models for a single decision.
- But, what happens when the different classifiers disagree?
- How do we separate the available training data for each classifier?
- Should the classifiers be learned jointly or in silos?
- Examples
  - Bagging
  - Boosting
  - Neural Networks (?)

SO MANY QUESTIONS...

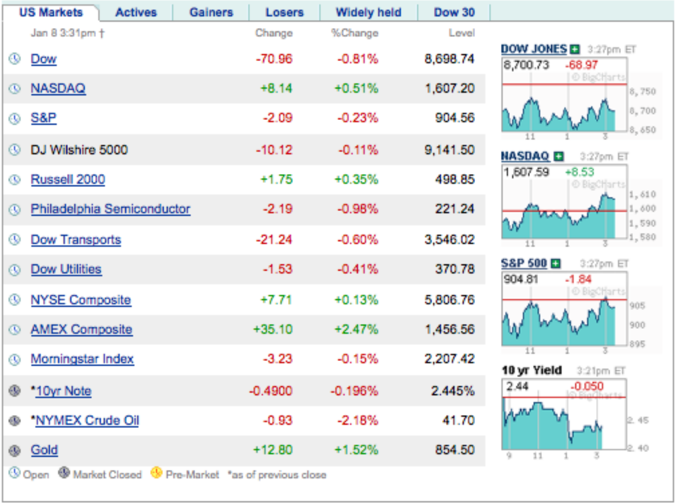
Examples of Pattern Recognition in the Real World

Hand-Written Digit Recognition



Examples of Pattern Recognition in the Real World

Computational Finance and the Stock Market



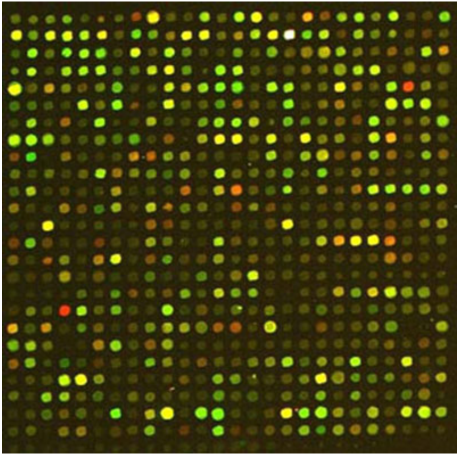
US Markets | Actives | Gainers | Losers | Widely held | Dow 30

Jan 8 3:31pm †	Change	%Change	Level
Dow	-70.96	-0.81%	8,698.74
NASDAQ	+8.14	+0.51%	1,607.20
S&P	-2.09	-0.23%	904.56
DJ Wilshire 5000	-10.12	-0.11%	9,141.50
Russell 2000	+1.75	+0.35%	498.85
Philadelphia Semiconductor	-2.19	-0.98%	221.24
Dow Transports	-21.24	-0.60%	3,546.02
Dow Utilities	-1.53	-0.41%	370.78
NYSE Composite	+7.71	+0.13%	5,806.76
AMEX Composite	+35.10	+2.47%	1,456.56
Morningstar Index	-3.23	-0.15%	2,207.42
*10yr Note	-0.4900	-0.196%	2.445%
*NYMEX Crude Oil	-0.93	-2.18%	41.70
Gold	+12.80	+1.52%	854.50

Open Market Closed Pre-Market *as of previous close

Examples of Pattern Recognition in the Real World

Bioinformatics and Gene Expression Analysis



Examples of Pattern Recognition in the Real World

Biometrics

High contrast print

Typical dry print

Faint print

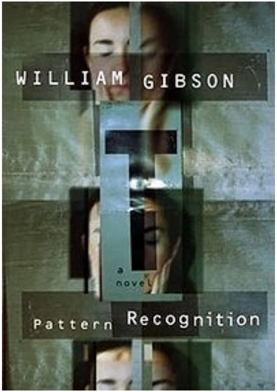
Low contrast print

Typical Wet Print

Creases

Examples of Pattern Recognition in the Real World

It is also a Novel by William Gibson!



Do let me know if you want to borrow it!