Speech Processing Overview & Supporting Concepts

Professor Marie Roch

Readings are listed in the schedule

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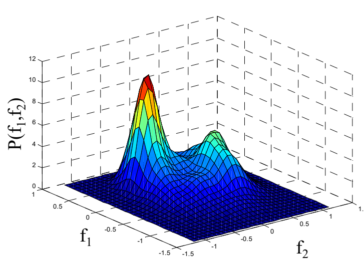
What is speech processing?

- Specialized branch of machine learning
- Interdisciplinary
  - signal processing
  - statistics
  - linear algebra
  - linguistics
  - optimization
  - perception & production



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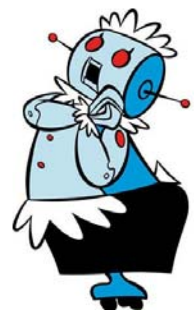
Basic ideas

- Acquire an audio signal
- Extract features
- Classify features to labels depending on goals, e.g.
  - text to speech
  - identify a person
  - recognize directives



Rosie the robot, The Jetsons © Hannah Barbera

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Probability

- A measure of uncertainty.
- Sources of uncertainty:
  - Process is stochastic (nondeterministic).
  - We cannot observe all aspects of process.
  - Incomplete modeling of process.

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Probability

Two ways to think about:

- frequentist – Related to the proportion of events occurring
- Bayesian – Related to degree of belief

Both types of probability are treated using the same rules.

Random variables

- Variables that can be bound to values non-deterministically.
- Common to use notation to distinguish between*
  - a random variable X (capitalized)
  - and an observed value x (lower case, e.g. x=5)

*Goodfellow et al. use bold in place of capitalization.

Discrete random variables

- Values from a discrete set of labels:

  $X \in \{\text{red, orange, yellow, blue, indigo, violet}\}, Y \in \{0,1,2\}$

- Probability density (mass) function (pdf/pmf) is the probability of something occurring, P(X=x)*:

  $P(X = red) = 0.8, P(Y = 2) = \frac{1}{3}$

- $\forall x \in \text{domain}(X), 0 \le P(X = x) \le 1 \text{ and } \sum_{x \in \text{domain}(X)} P(X = x) = 1$

*Goodfellow et al. use PMF for discrete distributions. P(X=x) is commonly abbreviated to P(x)

Distribution

- Set of probabilities associated with the values of a random variable.
- Uniform distribution – Special distribution where all probabilities are equal.

Example

- Let X be a die roll
  - P(X=3) denotes the probability of rolling a 3
  - Fair die → P(X=3) = 1/6

- If we don't know if the die is fair, how would we approximate P(X=x)?

- Estimates of probability are denoted with a hat:

$$\hat{P}(X = x)$$

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Continuous random variables

- Values from a continuous domain
- Satisfies the following:

$$\forall x \in \text{domain}(X), 0 \le P(X = x)$$

$$P(a \le X \le b) = \int_a^b P(X = x)dx$$

$$\int_x P(X = x)dx = 1$$

- Worth noting:
  - no max on P(X=x)
  - What is? $P(a \le X \le a) = \int_a^a P(X = x)dx$

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Continuous uniform distribution

$$X \sim U(a,b)$$

$$\text{implies } P(X = x) = \begin{cases} 0 & x < a \text{ or } x > b \\ \dfrac{1}{b-a} & a \le x \le b \end{cases}$$

In general, ~ means "has a distribution of."
U(a,b) is a uniform distribution between values and b

Expectation

discrete: $E[u(X)] = \sum_x u(x)\,\mathrm{P}(x)$

continuous: $E[u(X)] = \int_x u(x)\,\mathrm{P}(x)dx$

When u(X) = X, we call this the mean, or average value:

$$\mu = E[X]$$

Sample mean $\hat{\mu}$

- What if we don't know P(X=x)?
- If we roll a die many times, we can estimate P(X=x) by counting the number of times each x occurs and dividing by the number of rolls.

- To think about: How does this relate to our traditional idea of an average?

Variance

- Answers the question: What is the expected squared deviation from the mean?

- Can be defined with expectation operator

$$E[(X-\mu)^2] = \sum_x (x-\mu)^2 P(X=x)$$

- Sample variance (unbiased)

$$\hat{E}[(x-\mu)^2] = \frac{1}{N-1}\sum_x (x-\mu)^2$$

Normal distribution

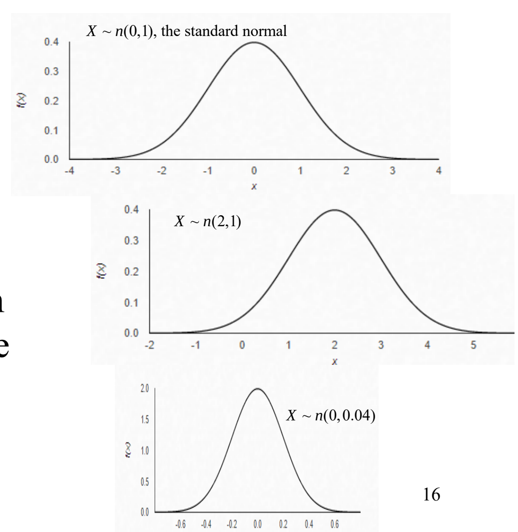
- Normal or Gaussian distributions are the so-called “bell curve” distributions
- Parameters: mean & variance: $X \sim n(\mu, \sigma^2)$

$$P(x \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

Normal distribution

- Mean controls the center, variance the breadth of the distribution.

- A normal distribution can be fit with sample mean & variance



Application: Speech/noise segmentation

How can we determine if someone is talking?

1. Record: Acquire pressure signal
2. Frame: Break into pieces
3. Compute features: root mean square intensity
4. Train: Fit speech/noise distribution models
5. Classify: See which distribution matches new samples

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Acquisition: pressure sensors

Basic ideas for microphones:

- Deformable membrane
  - pushed by compression
  - pulled by rarefaction
- Deformation is converted to voltage
- Samples: voltage measured N times/second and discretized
  - called sample rate (Fs) and
  - measured in Hertz (Hz)

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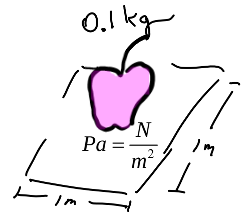
Pressure and Intensity

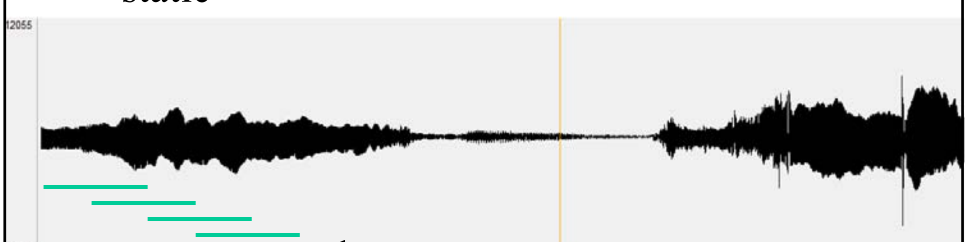
- Pressure
  - Amount of force per area
  - Typically measured in Pascals (Newtons/meter squared) if the microphone is calibrated otherwise in counts



- Intensity
  - Product of sound pressure and particle velocity per area
  - Pressure$^2 \alpha$ Intensity

Framing

- Most audio signals vary over time
- Analyze small segments that are roughly static



and so on…

chimpanzee pant hoot – courtesy Cat Hobaiter

decibel (dB) scale

- Human auditory sensitivity to *pressure*:

  20 μPa – 200 Pa (10[7] range!)
- The <u>deci</u>bel scale allows us to compare the *intensity* between two sounds in a compressed range:
  - Intensity $10\log_{10}\left(\dfrac{I}{I_0}\right)$
  - ~ with pressure $10\log_{10}\left(\dfrac{P}{P_0}\right)^2 = 20\log_{10}\left(\dfrac{P}{P_0}\right)$

What value of P_0?

calibrated terrestrial systems:

$P_0 = 20\mu\text{Pa}$ (threshold of hearing)

denoted dB re 20 μPa

uncalibrated systems:

$P_0 = 1$ (for convenience)

denoted dB rel.

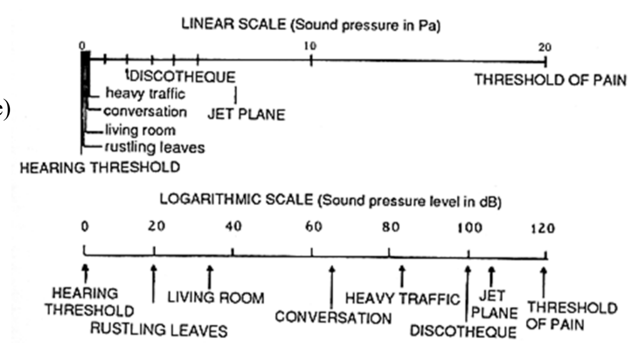


Figure 2.4 Intensities of some different sounds given in linear and logarithmic measures. (From Spens, 1970.)

Rabiner/Juang 1993

Computing intensity

- Computed for each frame
- Root-mean-square (RMS) pressure
  - squared
  - averaged
  - square root

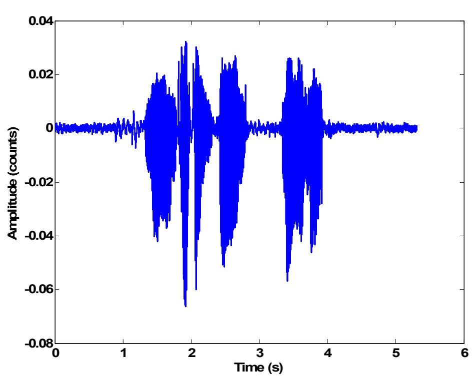
$$p_{RMS} = \sqrt{\frac{1}{|\text{frame}|} \sum_{i \in \text{frame}} x_i^2}$$

- Pressure converted to intensity in dB:

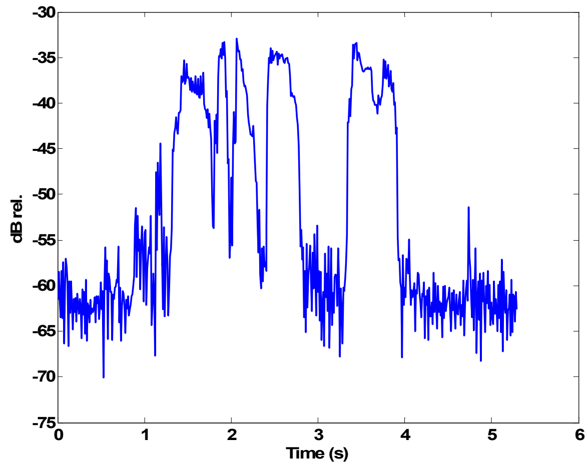
$$20 \log_{10}(p_{RMS}) = 10 \log_{10}\left(\frac{1}{|\text{frame}|} \sum_{i \in \text{frame}} x_i^2\right) \text{ dB}$$

Our first speech problem

- Given a recording, separate speech from constant background noise



Relative Intensity



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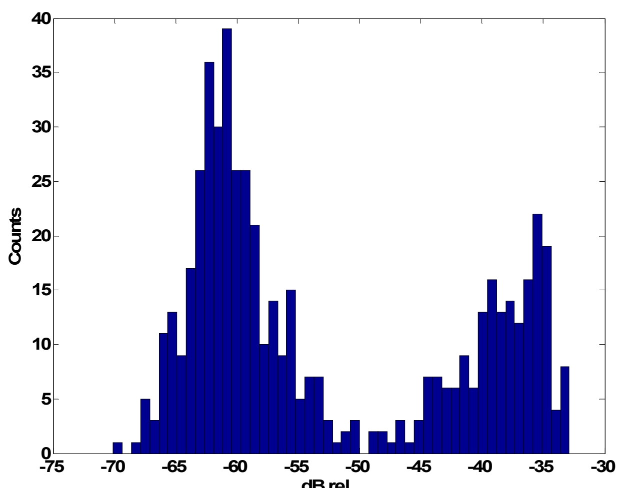
Intensity histogram



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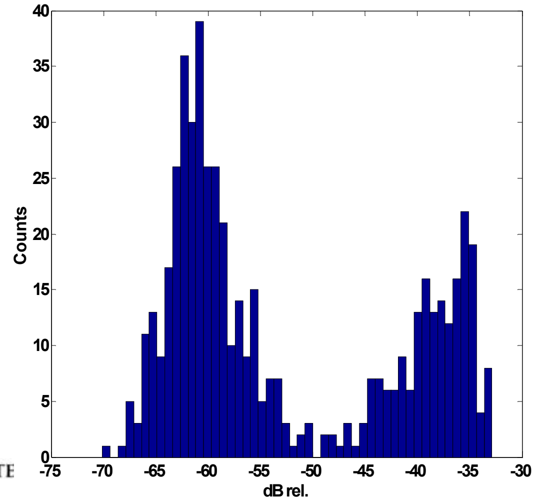
So how can we characterize speech and silence?



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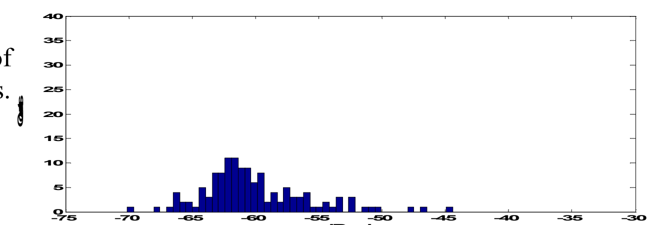
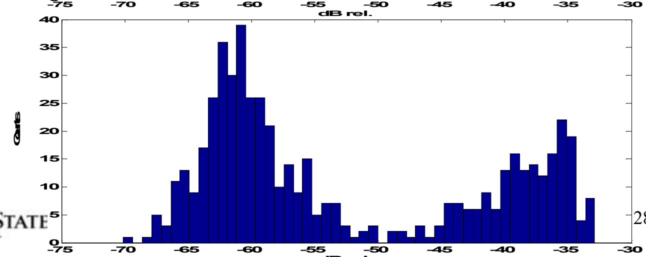
Silence estimator

- Beginning of recording vs.



- Entire recording



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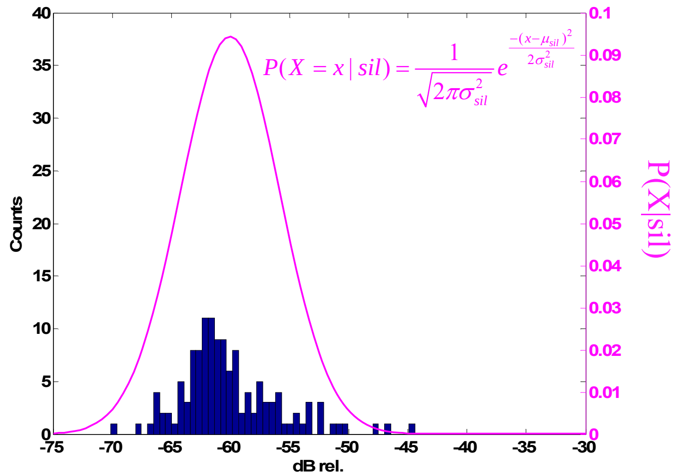
Normal fit of silence



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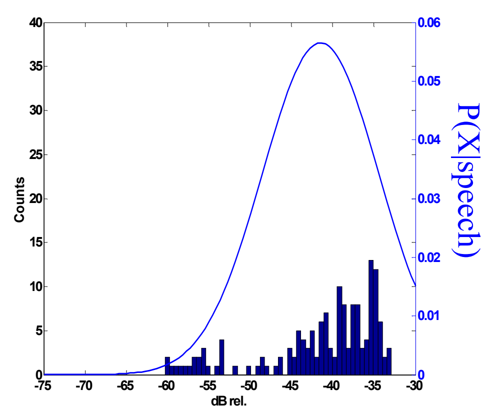
Similar for speech 1.3 – 2.8 s



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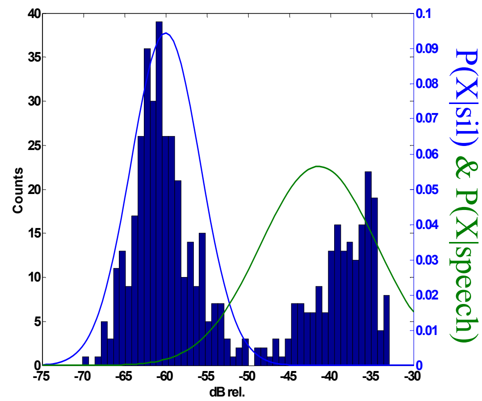
Intensity distribution with pdfs



Where should we draw the boundary?

Conditional probability

The probability of something occurring can change when you know something…

$$P(X = \text{"nice to meet you"})$$

vs

$$P(X = \text{"nice to meet you"} \mid \text{meeting new person})$$

Conditional probability

The probability of something occurring can change when you know something…

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Formally, P(X|Y) defined as:

$$P(X \mid Y) \triangleq \frac{P(X,Y)}{P(Y)}$$

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A problem…

Our intensity pdfs showed

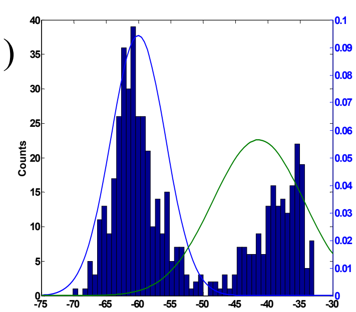
$$P(X \mid speech) \text{ and } P(X \mid noise)$$

but we would like to know

$$P(speech \mid X) \text{ and } P(noise \mid X)$$

which is known as the

posterior distribution



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Reverend Thomas Bayes
1702-1761

Bayes' decision rule

The optimal classification rule is the one that maximizes the posterior probability:

$$\arg\max_{\omega \in \{speech, noise\}} P(\omega \mid X)$$

Regrettably, we do not know $P(\omega \mid X)$,
but we do know $P(X \mid \omega)$

note: arg returns the argument (ω) rather than the value

Bayes' rule

(of conditional probability)

$$P(A \mid B) = \frac{P(A, B)}{P(B)} \triangleq \text{ conditional probability}$$

note that swapping names A and B

$$\text{P(B|A)}=\frac{P(B, A)}{P(A)} \rightarrow P(B, A) = P(B \mid A) P(A)$$

and $P(A, B) = P(B, A)$

$$\therefore P(A \mid B) = \frac{P(B \mid A) P(A)}{P(B)}$$

Bayes' Rule
≠Bayes' Decision Rule

also known as Bayes' Theorem/Bayes' Law)

Bayes' decision rule

Bayes' rule to the rescue!

class-conditional probability

prior probability

$$\arg\max_{\omega} P(\omega \mid X) = \frac{P(X \mid \omega)P(\omega)}{P(X)}$$

posterior probability

observation probability

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almost there…

$$P(\omega \mid X) = \frac{P(X \mid \omega)P(\omega)}{P(X)}$$

We know P(X|ω). We don't need to know P(X) as

$$\max\left(\frac{P(X \mid speech)P(speech)}{P(X)}, \frac{P(X \mid noise)P(noise)}{P(X)}\right)$$

$$= \max\left(P(X \mid speech)P(speech), P(X \mid noise)P(noise)\right)$$

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Prior probability

- Probability of an observation without any prior information.
- When we don't know this, we frequently assume a uniform (equally likely) distribution:

$$= \max\left(P(X \mid speech)\frac{1}{2}, P(X \mid noise)\frac{1}{2} \right)$$

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Bayes decision rule revisited

Assuming a uniform prior, we can now make decisions about speech or noise:

$$\text{decision}(x) = \underset{\omega \in \{speech, noise\}}{\arg\max} \frac{1}{\sqrt{2\pi\sigma_\omega^2}} e^{\frac{-(x-\mu_\omega)^2}{2\sigma_\omega^2}}$$

How can we solve the boundary threshold?

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Threshold for our minimal speech detector

Solve for x (2 roots):

$$\frac{1}{\sqrt{2\pi\sigma_{noise}^2}} e^{\frac{-(x-\mu_{noise})^2}{2\sigma_{noise}^2}} = \frac{1}{\sqrt{2\pi\sigma_{speech}^2}} e^{\frac{-(x-\mu_{speech})^2}{2\sigma_{speech}^2}}$$

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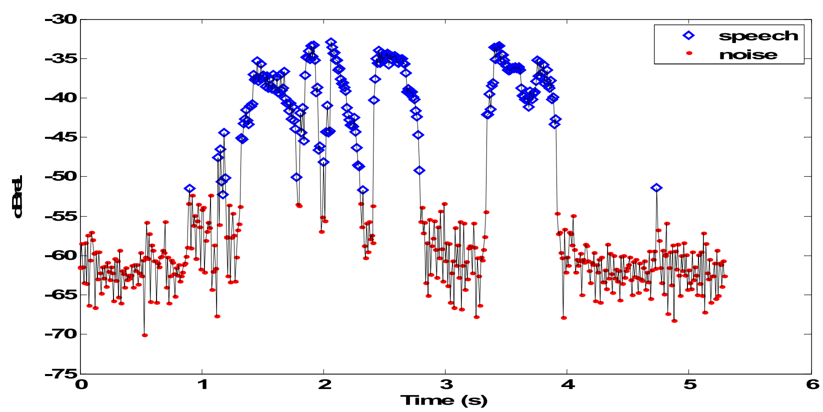
Result



Caveat: Example is for pedagogical purposes, we can do better than this…

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A brief introduction to Python

- Object oriented language
- Weak typing system, variables do not need to be declared
- Nice language for rapid prototyping
- Rich set of standard libraries and add-ons

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Basics

- Indentation is part of the language
- Commands end at line feed unless continuation character present: \
- From # to end of line is a comment

- Be sure to comment your code!

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Basic types

- boolean: True/False
- int, float, complex
- string ‘hi there’ or “hi there”
- sequences:
  - lists: [4, 5, 10, “alpha”]
  - tuples: (4, 5, 10, “alpha”)

  Tuples are static, you cannot append, delete, etc.

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Basic types

- Sets: set([3,4,3,5]) → {3, 4, 5}
- Dictionaries (hash tables)
  - >>> mydict = {} # empty dictionary
  - >>> mydict["hello"] = "hola"
  - >>> mydict["goodbye"] = "adios"

- >>> mydict
- {'hello': 'hola', 'goodbye': 'adios'}
- >>> mydict['goodbye']
- 'adios'
- >>> mydict['restroom']
- Traceback (most recent call last):
- File "<stdin>", line 1, in <module>
- KeyError: 'restroom'

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Loops

for x in range(10):
        print(x) # 0:9
for x in range(3,10):
        print(x) # 3:9

for supports iterators, e.g. iterating over a list variable

x = 3
while x < 10:
        print(x)

Loops support:
- continue
- break

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Functions

```
def classify(model, examples):
      '''classify – Classify each example
      model is classifier, examples are list
      of feature lists/tuples
      '''
      labels = []  # empty label list
      # predict class and store result
      for ex in examples:
            label = model.predict(ex)
            labels.append(label)
      return labels
```

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Objects

```
class classifier:
      def __init__(self):
            ''' documentation string
            '''
            # constructor code
      def train(self, examples, labels):
            # code to train, e.g.
            self.model = …
      def predict(self, example)
            return self.model.predict(example)
```

Note: self is declared explicitly
Equivalent to this in C++/Java

Objects

- Objects support class and instance variables, we only showed instance variables (look it up)
- Private methods, use __name
- Special methods, use __name__

Objects

- Some special methods
  - __iter__(self) – Returns an iterator object. If the object can do iteration, sometimes just returns self
  - __next__(self) – Returns the next item. When there are no more items, executes "raise StopIteration"

Iterator example

```
class Fib:
    '''iterator that yields numbers in the Fibonacci sequence, series where next number is sum
      of the previous two'''

    def __init__(self, max):
        self.max = max      # stop when next Fibonacci number exceeds this

    def __iter__(self):
        self.a = 0
        self.b = 1
        return self

    def __next__(self):
        fib = self.a
        if fib > self.max:
            raise StopIteration
        self.a, self.b = self.b, self.a + self.b  # evaluate RHS first, then assign pair
        return fib
```

Example from Pilgrim's *Dive Into Python 3*

Exceptions

```
try:
        some code…
except RunTimeError as e:
        e is bound to the exception object
        do what you want…

# Other exceptions are not caught
# Read about finally clause
```