Replace yourself with a very small shell script

Stefanie Schirmer
@linse

this slide is just for the clock

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Hi, I am Steffi and I still work at etsy.com. :D

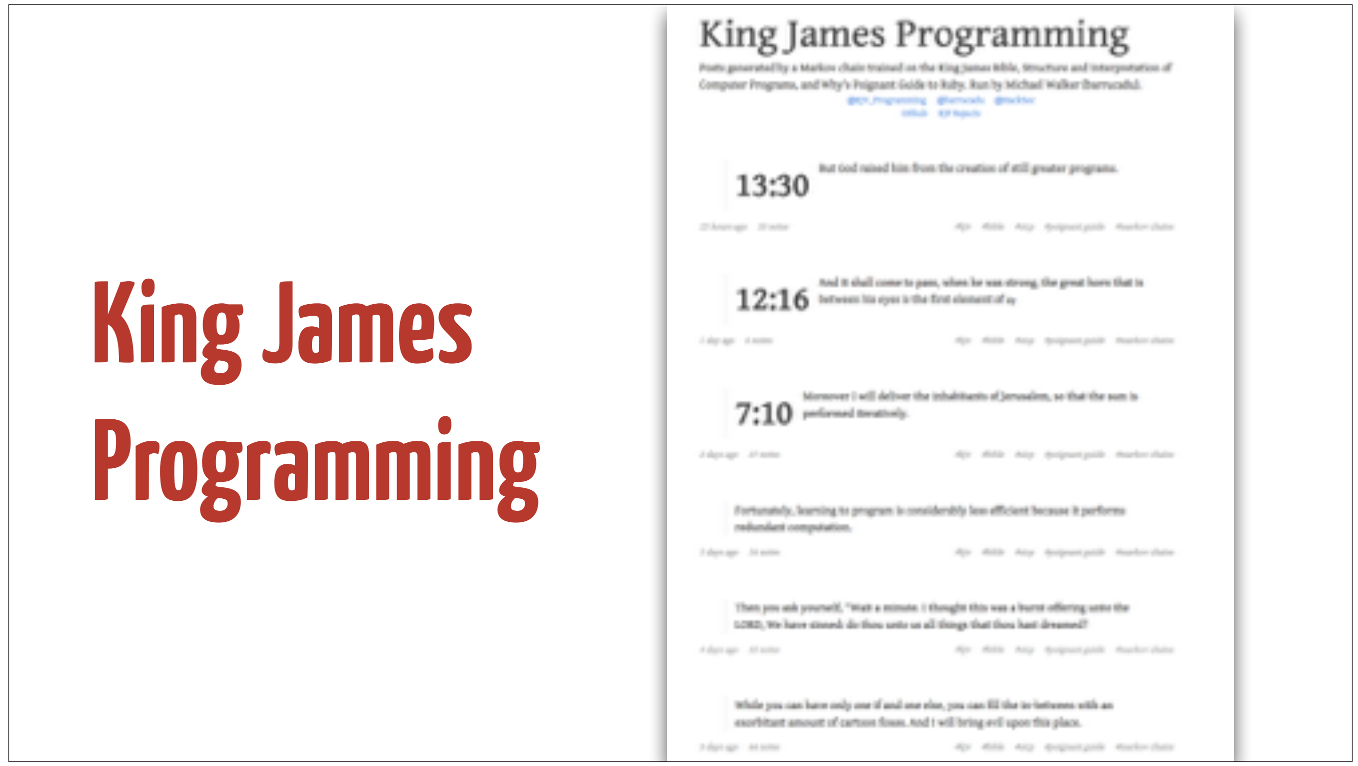
To make my life easier, I'd like to replace myself with a very small shell script.

Replace yourself with a very small shell script

~~Stefanie Schirmer~~
@linse_ebooks

This is linse ebooks, and she’s taking over from now on.

Recently, there has been an outbreak of markov bots.



There is for example the king james programming site, where somebody mixed the king james bible, structure and interpretation of computer programs, and some ruby guide.

the mix brings up something like:

while you can have only one ifa nd else, you can fill the in-between with an exorbitant amount of cartoon foxes. and I will bring evil upon this place.

There is a mix of the works of HP Lovecraft and the puppet manual:

Things-presences or voices of some sort could be drawn down from unknown places as well as to standard out.

And then there is the Erowid Recruiter, which is a mix of drug use reports and recruiter email spam.

PHP, Python or Perl, years of experience with psychedelic hallucinations.

The easy way

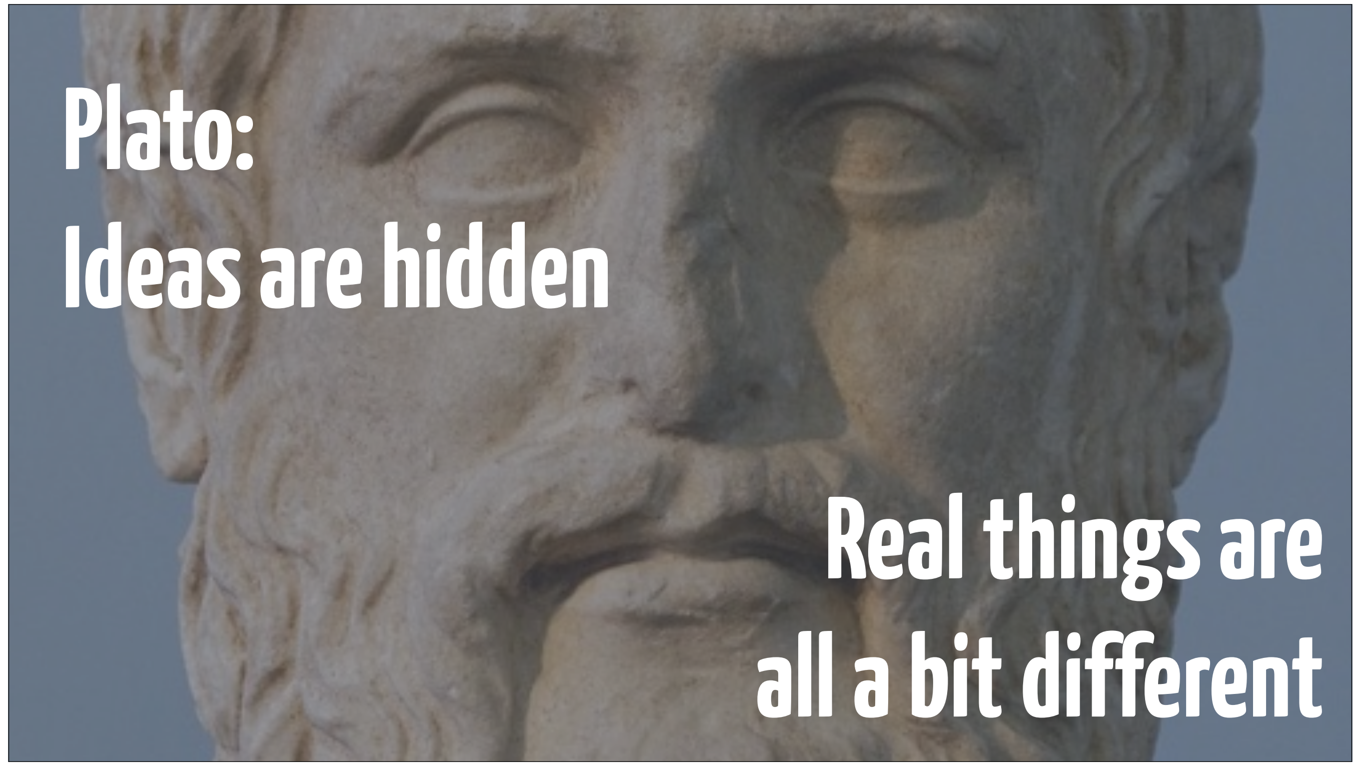
For my bot on twitter, linse_ebooks, I used the easy way. A premade library from user “abadidea” on twitter.

On github it is mispy - twitter-underscore-ebooks.

A ruby script can be used to download all your tweets, consume them and build a model, and produce new tweets.

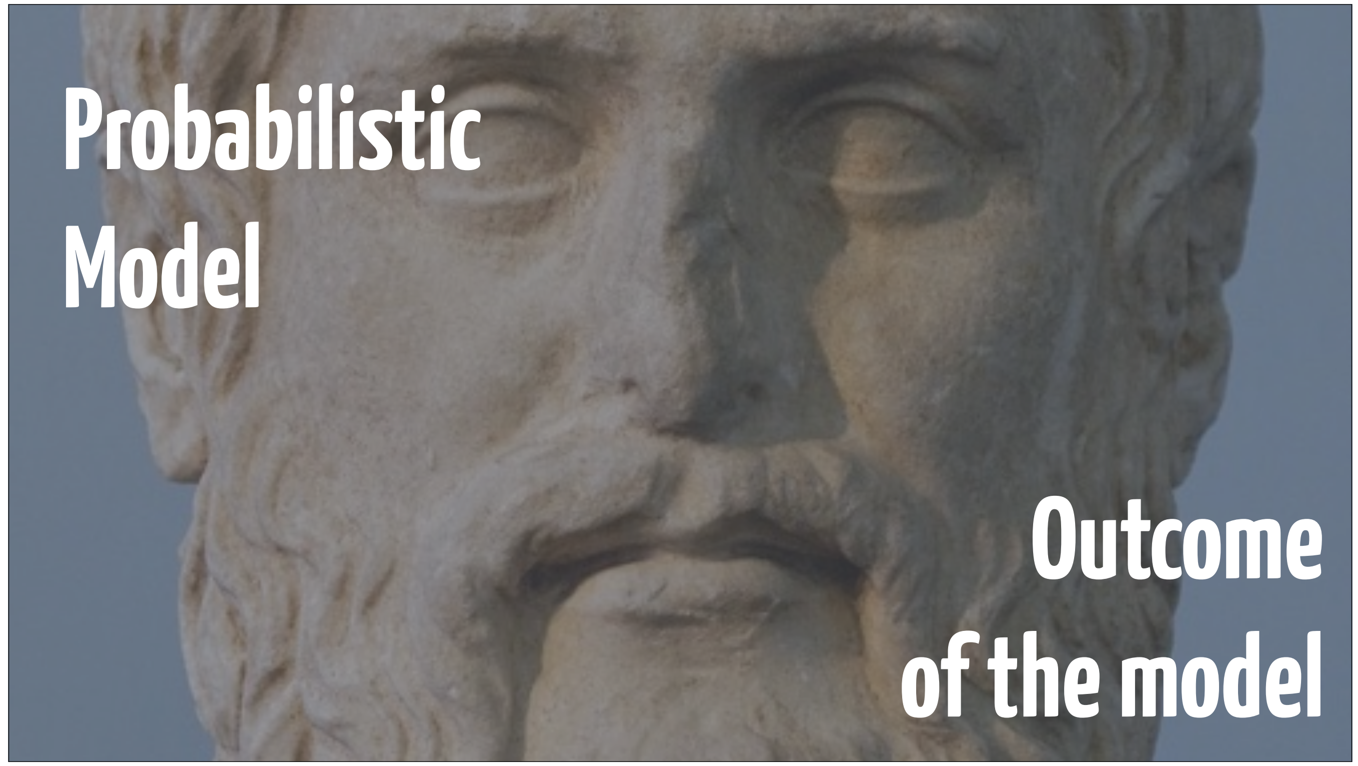
You just have to enter your and the bot’s account details and run the script.

But of course I wanna know how this works.
In my life before Etsy I tried to predict the foldings of molecules with a statistical model. Maybe we can build such a model for writings by humans?



Let's time travel a bit.

Plato is well known for his theory of the world of ideas. Think of the idea of a perfect circle, it's totally possible for us to imagine it, but it's impossible for me to draw one. Each real one will be a bit different.



We could say the perfect circle is the idea, the model.

The outcome is what we see in the real world.

Can we do this for text? What’s the model for text? Or for a sentence?

Model for text:
n-gram probability

One of the simplest, but also very effective features to build a text model is the probability of words appearing in sequence. An n-gram is a subsequence of length n. For text this means two words in a row if we choose n to be two. This is also called a bi-gram.

What is the probability of the word apple followed by the word sauce?

What is the probability of the word apple followed by the word strudel?

What is the probability of word A followed by word B?

printBigrams.py

```
#!/usr/bin/python

import sys

fname = sys.argv[1]
previous = ''
with open(fname) as f:
    for line in f:
        for word in line.split():
            if previous != '':
              print previous, word
            previous = word
```

Let’s print out all bi-grams from the text.

We keep track of the previous word, and then it’s just a matter of looping through word by word, printing out the previous and the current word.

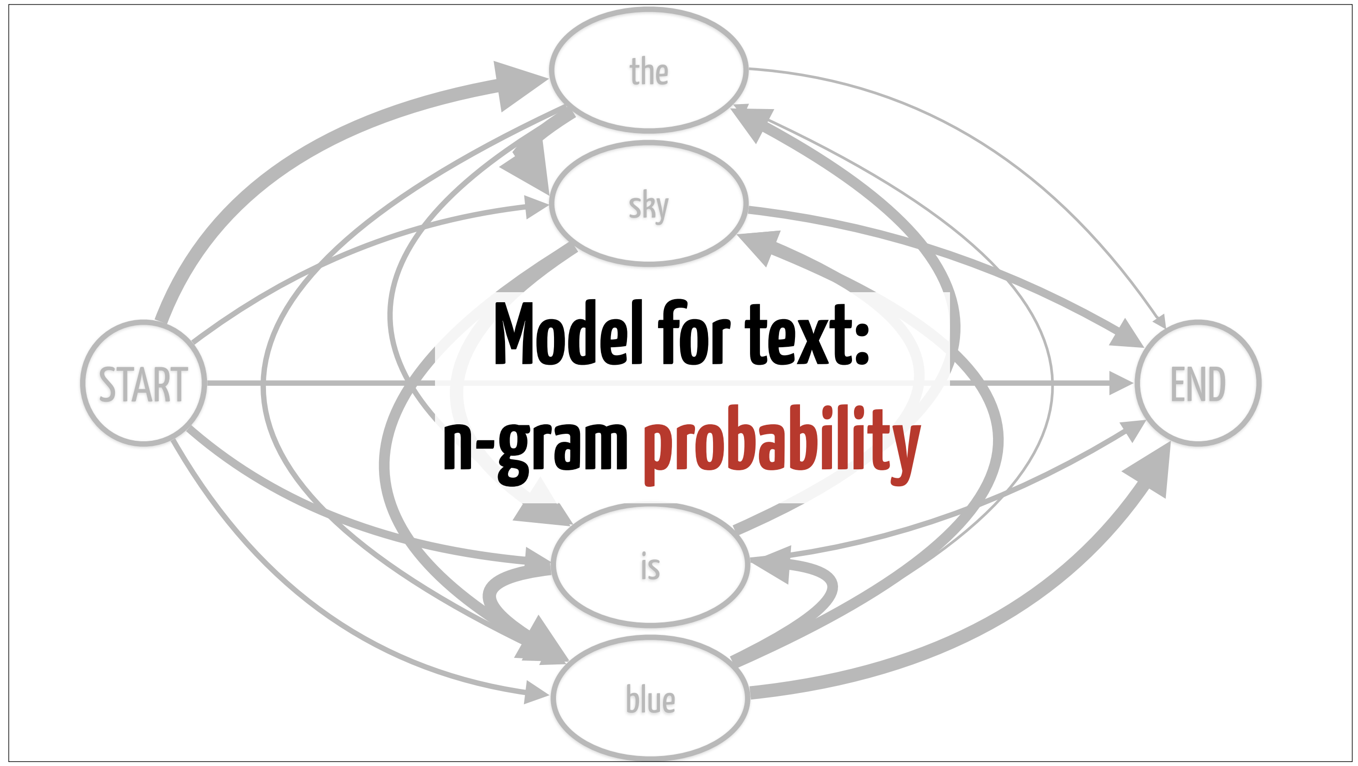
For the never-ending story it looks like this. But that’s another story and shall be told another time.

It’s just pairs of words for now.

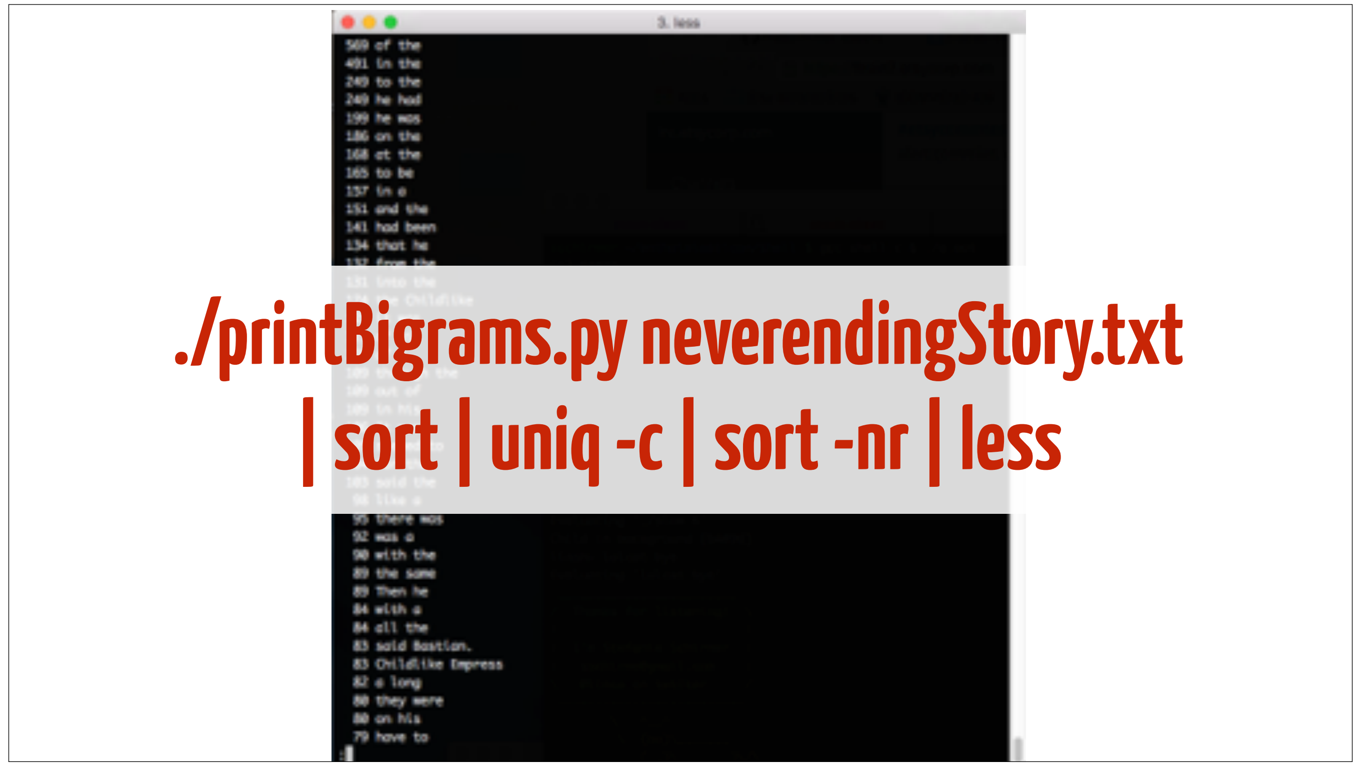
Model for text:
n-gram probability

We should sort them, and count them, to compute transition probabilities.

This is the learning step of our algorithm.



With the transition probabilities, we can imagine our text corpus like this weighted graph. Some paths through the graph are more or less likely to be found in real text. So let’s count the bi-grams.



Unix tools to the rescue! I can get a good first glance of the distribution by piping the bigrams into sort | uniq -c | sort -nr | less

record bi-grams -> model

check for sentences

```python
def allBigrams(bigrams,fname):
    previous = ''
    with open(fname) as f:
        for line in f:
            for word in line.split():
                if previous != '':
                    if previous.endswith(('.', '?', '!')):
                        bigrams = addBigram(bigrams, previous, 'END')
                        bigrams = addBigram(bigrams, 'START', word)
                    else:
                        bigrams = addBigram(bigrams, previous, word)
                previous = word
    return bigrams
```

To put all bigrams into a model data structure, instead of printing them, we use a dictionary called bigrams. The looping is the same as before.

Also, we take care of sentence beginnings and endings. We add a START and END state to indicate those. Adding START and END state makes a huge difference in how real the output sounds - because we mimic a sentence structure!

record one bi-gram

```
def addBigram(model, first, second):
    if not first in model:
        model[first] = {}
    if not second in model[first]:
        model[first][second] = 1
    else:
        model[first][second] = model[first][second]+1
    return model
```

How do we add a new bi-gram to our model?

The model is a two dimensional lookup structure, here a python dictionary.

It is indexed by the first and second word of the bi-gram. And it gives us the number of occurrences of this particular two words following each other in the text. For a new first word, we set up a new dict for that word.

For a new bigram, we set up a new dict entry with count one.

For a known bigram, we increment it’s count in the model.

Ok, our model is ready now!

How do we make it talk?

To generate text, we have to traverse the states of our model, according to the probabilities of the transitions.

Starting from a START state, I could travel into a “Hello” state, into a “there” state and an exclamation mark state and arrive at an END state, for example.

generate a sentence

```python
def main():
    # 1. learn model
    model = {}
    # skip program name
    for arg in sys.argv[1:]:
        model = allBigrams(model,arg)
    # 2. generate
    state = 'START'
    while state != 'END':
        state = step(model, state)
```

How do we write this in code?

Here you see we prepared the model. Here we can add a second input file.

Then, for the generation part, we start from the Start state.

And we make steps until we reach the end state.

The cool thing is that with our bi-gram model we don’t need to know anything besides the current state, in order to generate the next state. We have no knowledge of the past. This property is called memorylessness, or also called “the Markov property”. This keeps the model simple and elegant.

find next word

```
def step(model, state):
    nextStates = model[state].items()
    nextState = weighted_choice(nextStates)
    if not nextState=='END':
        print nextState,
    return nextState
```

In each step we pick a next state or word according to the distribution of the current word's successors that we counted in the text.

Let's make the weighted choice.

find next word

```
def weighted_choice(choices):
    total = sum(w for word, w in choices)
    r = random.uniform(0, total)
    upto = 0
    for word, w in choices:
       if upto + w > r:
          return word
       upto += w
    assert False, "Shouldn't get here"
```

We sample (or we could say choose or draw) the next word according to the distribution, depending on the number of words that can be reached from a word and how often they are seen.

By drawing randomly from the sum of all seen next words (summing up all counts), we can make a choice weighted by those counts.

Let’s try it out!

So let’s run our script and produce a sentence!

Starting from the Start state, we make steps until the sentence is complete and we have reached the end state.

Thank you!

I'm Stefanie Schirmer
sschirme@gmail.com
@linse on twitter