[301] Dictionary Nesting

Tyler Caraza-Harter

Learning Objectives Today

More dictionary operations

- len, in, for loop
- d.keys(), d.values()
- defaults for get and pop, defaultdict

makes coding more convenient

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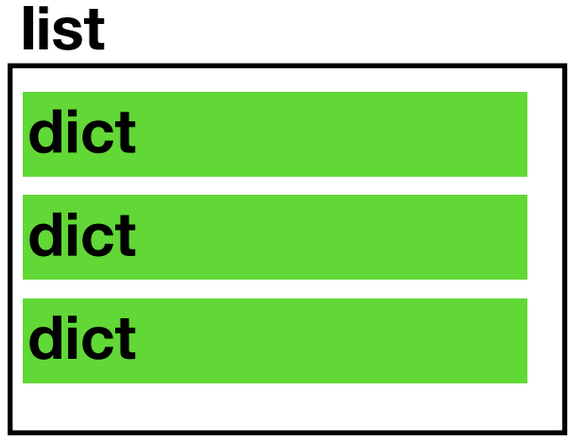
Syntax for nesting (dicts inside dicts, etc)

- indexing/lookup
- step-by-step resolution



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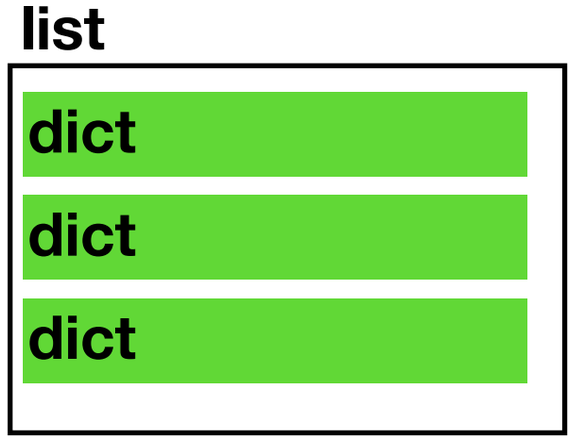

Understand common use cases for nesting

- transition probabilities with Markov chains (dict in dict)
- binning/bucketing (list in dict)
- a more convenient table representation (dict in list)

one of the most common data analysis tasks

we'll generate random English-like texts

Today's Outline

More Dictionary Ops

Probabilities Tables

Markov Chains (dict of dict)

Binning (dict of list)

Table Representation (list of dict)

Creation of Empty Dict

Non-empty dict:

```
d = {“a”: “alpha”, “b”: “beta”}
```

Empty dict (way 1):

```
d = {}
```

Empty dict (way 2):

```
d = dict()
```

Creation of Empty Dict

Non-empty dict:

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d = {“a”: “alpha”, “b”: “beta”}
```

Empty dict (way 1):

```
d = {}
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Empty dict (way 2):

```
d = dict()
```

Similar for Lists

```
empty_list_1 = []
empty_list_2 = list()
```

len, in, for

```
num_words = {0:“zero”, 1:”one”, 2:”two”, 3:”three”}

print(len(num_words))

print(1 in num_words)

print(“one” in num_words)

for x in num_words:
    print(x)
```

len, in, for

```
num_words = {0:“zero”, 1:”one”, 2:”two”, 3:”three”}

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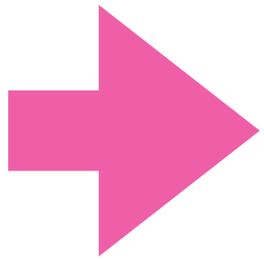

4

len, in, for

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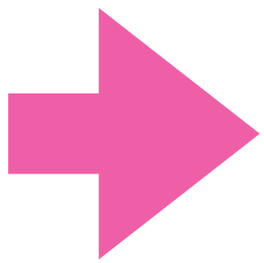

4

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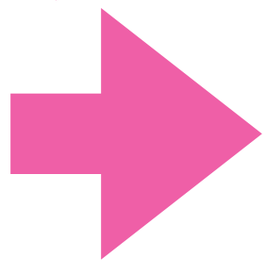

True

```
print(“one” in num_words)
```

```
for x in num_words:
    print(x)
```

len, in, for

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```
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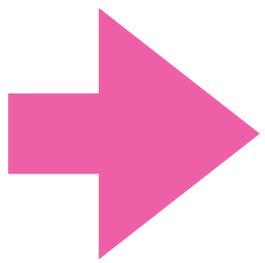

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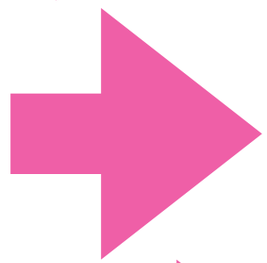

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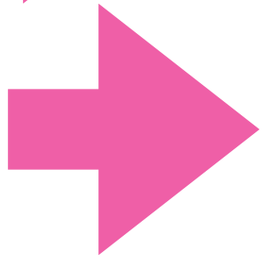

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(it is only checking keys, not vals)

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for x in num_words:
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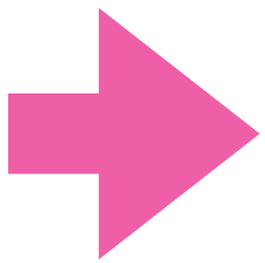

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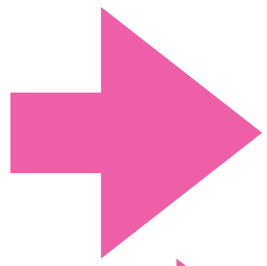

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print(“one” in num_words)
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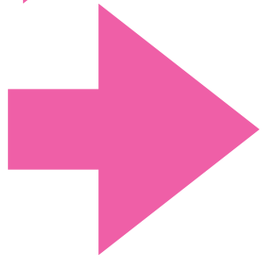

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for x in num_words:
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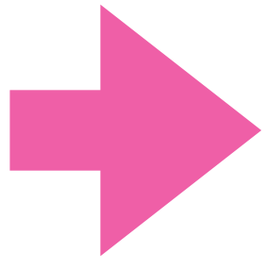


2
1
0
3

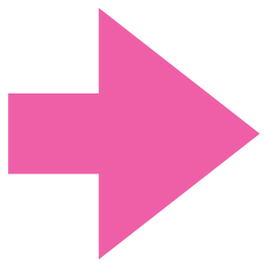
(for iterates over keys, not vals)

(note there is no order here)

len, in, for

```
num_words = {0:“zero”, 1:”one”, 2:”two”, 3:”three”}
```

```
print(len(num_words))
```



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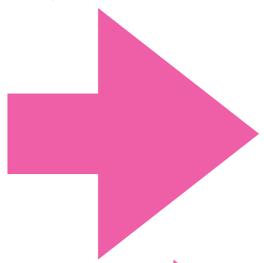

True

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print(“one” in num_words)
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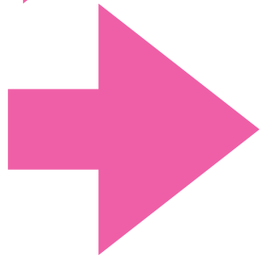
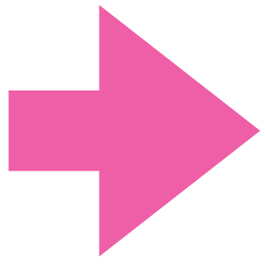


False

(it is only checking keys, not vals)

```
for x in num_words:
    print(x, num_words[x])
```



2 two
1 one
0 zero
3 three

you can iterate over values
by combining a for loop with lookup

Extracting keys and values

```
num_words = {0:“zero”, 1:”one”, 2:”two”, 3:”three”}

print(type(num_words.keys()))

print(type(num_words.values()))
```

Extracting keys and values

```
num_words = {0:“zero”, 1:”one”, 2:”two”, 3:”three”}
```

```
print(type(num_words.keys()))
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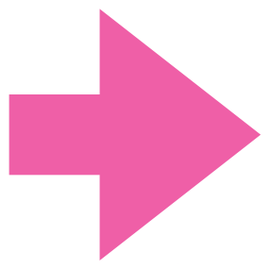
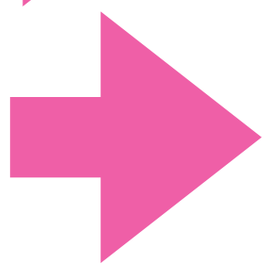


<class 'dict_keys'>

```
print(type(num_words.values()))
```



<class 'dict_values'>

don’t worry about these new types, because we can force them to be lists

Extracting keys and values

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num_words = {0:“zero”, 1:”one”, 2:”two”, 3:”three”}
```

```
print(type(num_words.keys()))
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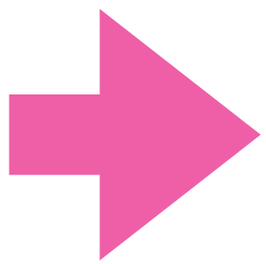

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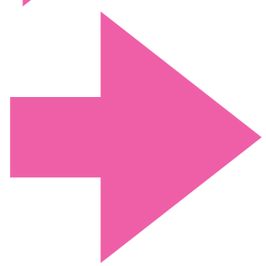
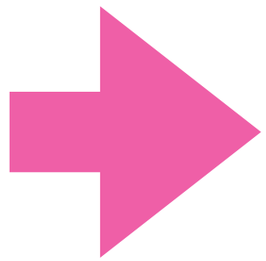


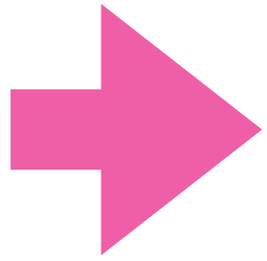
<class 'dict_values'>

```
print(list(num_words.keys()))
```



[3, 1, 2, 0]

```
print(list(num_words.values()))
```



[“one”, “two”,
“zero”, “three”]

Defaults with get and pop

```
suffix = {1:“st”, 2:”nd”, 3:”rd”}

suffix.pop(0) # delete fails, because no key 0

suffix[4] # lookup fails because no key 4

suffix.get(4, “th”) # returns “th” because no key 4
```

specify a default if key cannot be found

Defaults with get and pop

```
suffix = {1:“st”, 2:”nd”, 3:”rd”}
suffix.pop(0) # delete fails, because no key 0
```

specify a default if
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```
suffix[4] # lookup fails because no key 4
suffix.get(4, “th”) # returns “th” because no key 4
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Defaults with get and pop

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specify a default if
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```
suffix.pop(0, “th”) # returns “th” because no key 0


suffix[4] # lookup fails because no key 4
```

```
suffix.get(4, “th”) # returns “th” because no key 4
```

specify a default if
key cannot be found

Defaults with get and pop

```
suffix = {1:“st”, 2:”nd”, 3:”rd”}


for num in range(6):
    print(str(num) + suffix.get(num, “th”))
```

Defaults with get and pop

```
suffix = {1:“st”, 2:”nd”, 3:”rd”}


for num in range(6):
    print(str(num) + suffix.get(num, “th”))
```

0th
1st
2nd
3rd
4th
5th

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Probabilities Tables

Markov Chains (dict of dict)

Binning (dict of list)

Table Representation (list of dict)

Weighted Random

```
transitions = {
    “up”: 0.2,
    “down”: 0.1,
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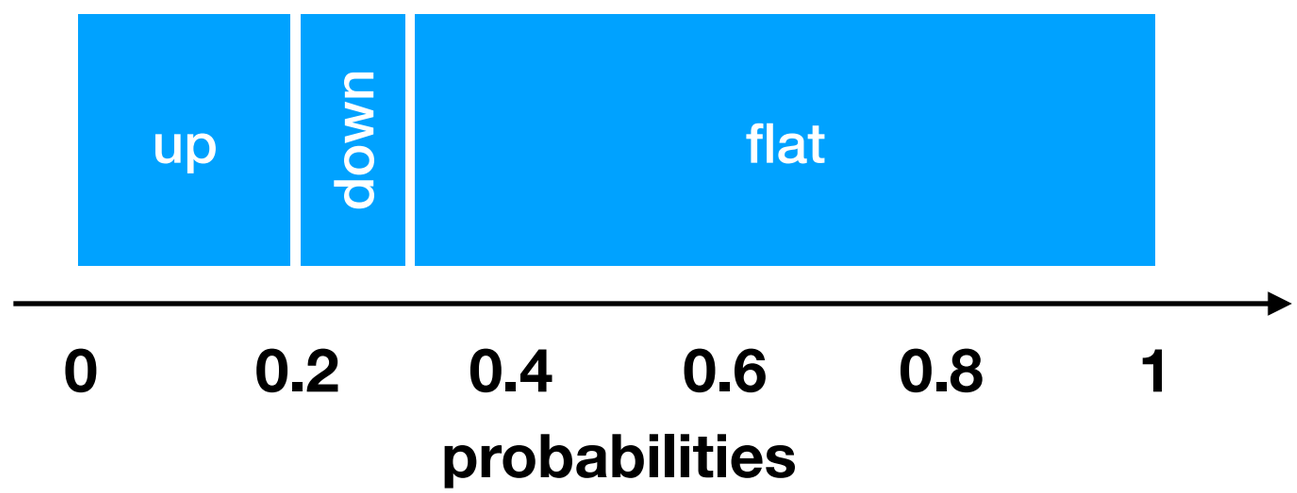

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transitions = {
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x = random.random()
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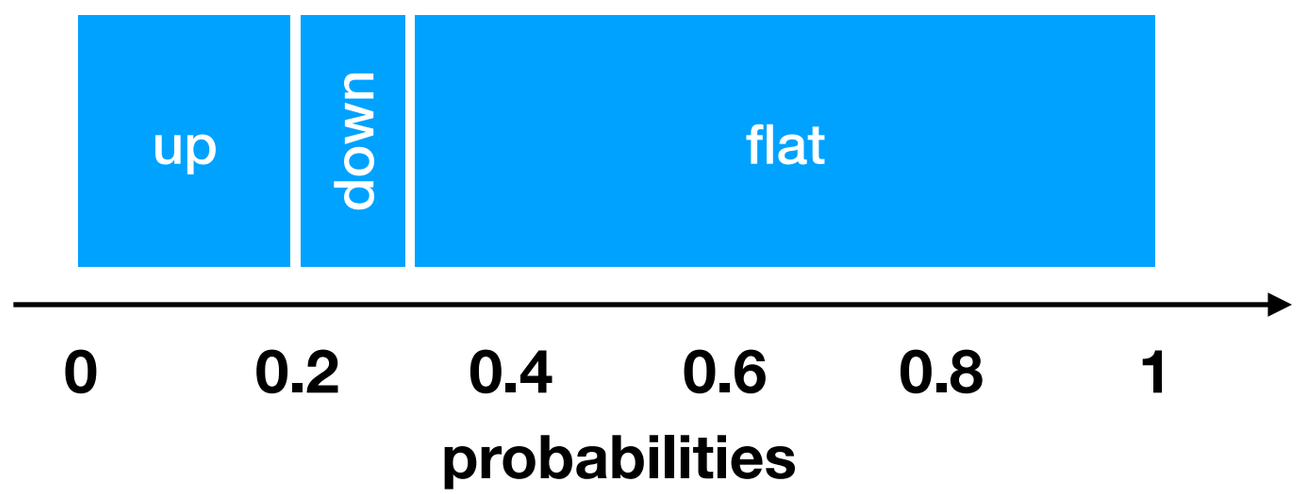

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x = random.random()
# assume 0.5
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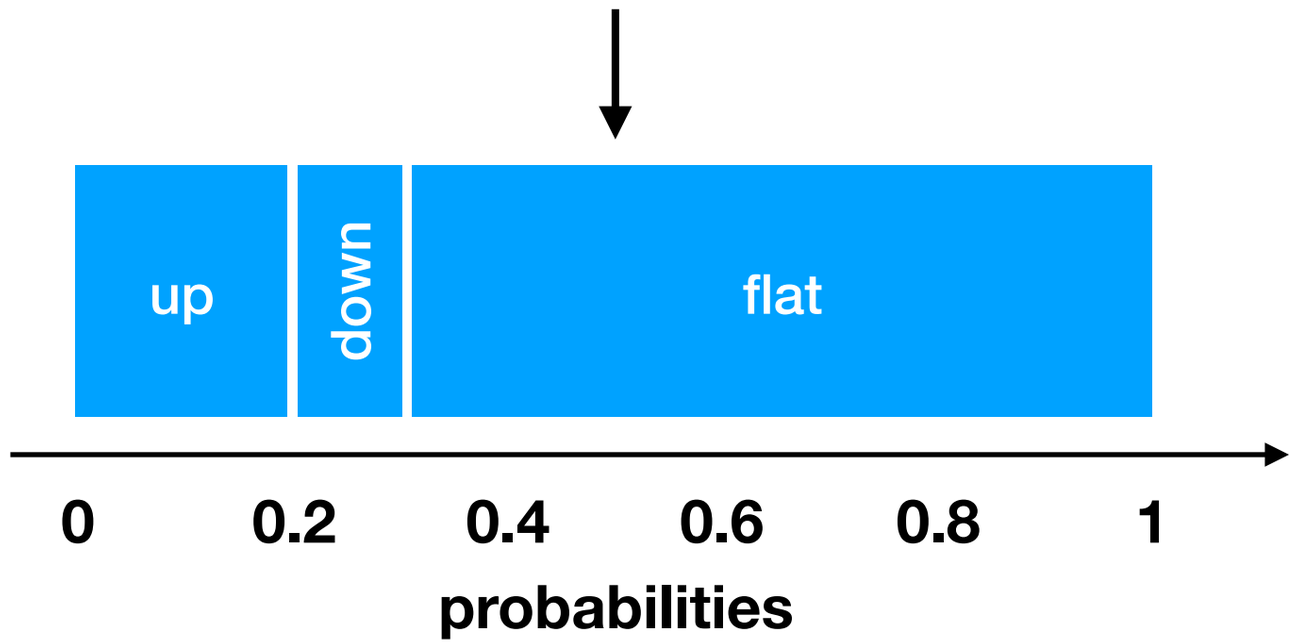

Weighted Random

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transitions = {
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```
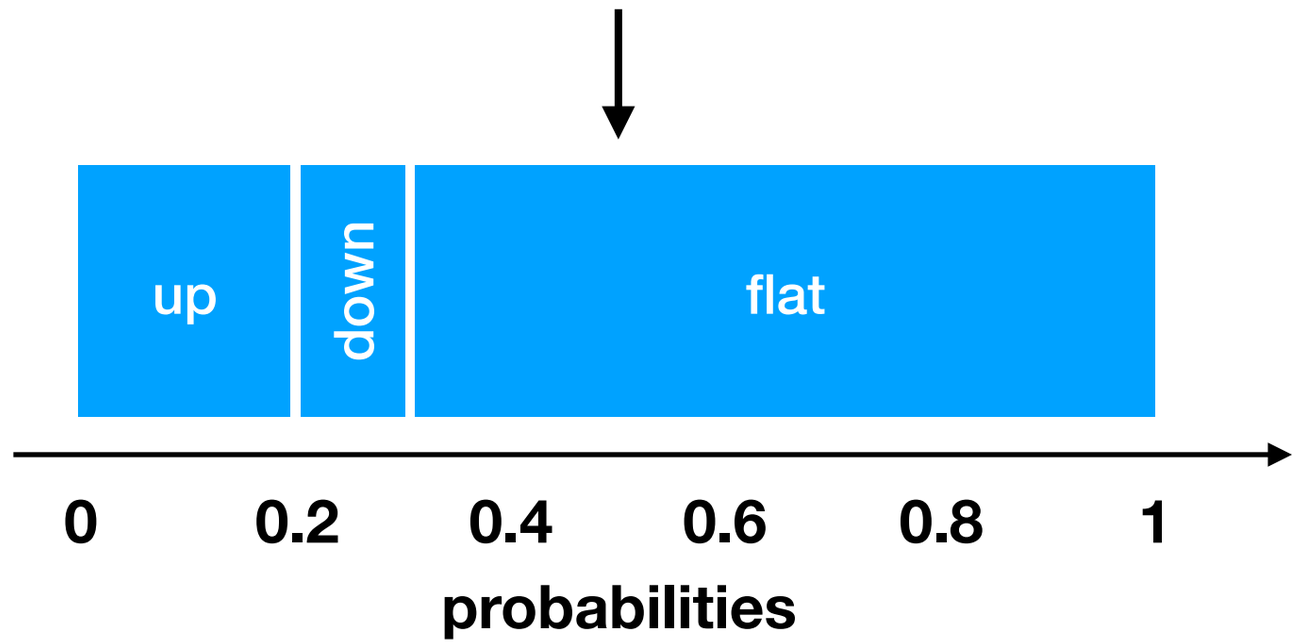

flat “wins”



Weighted Random

```
transitions = {
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}


x = random.random()
# assume 0.25
```

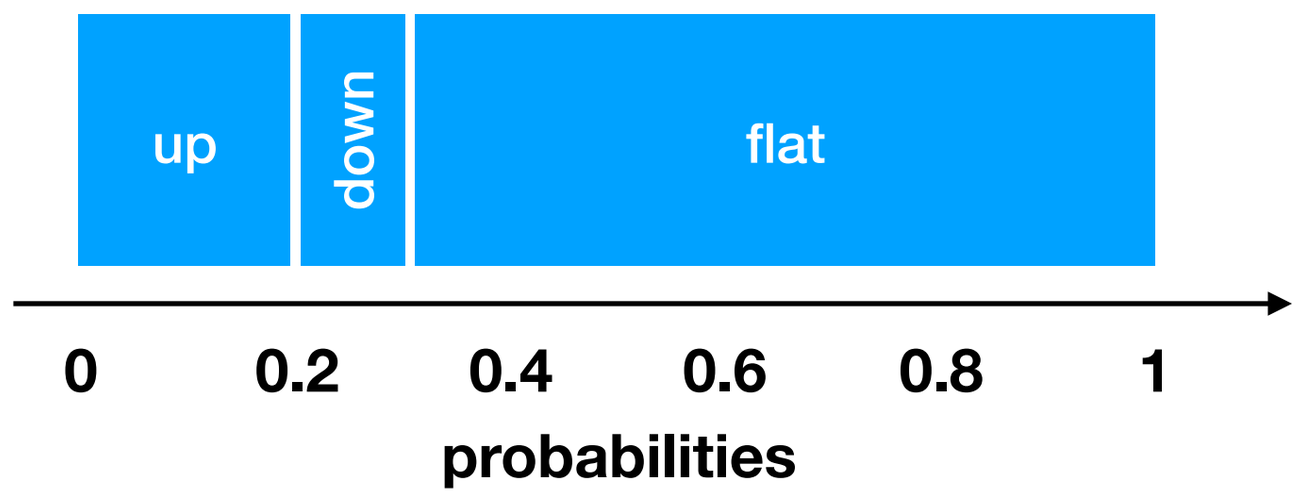

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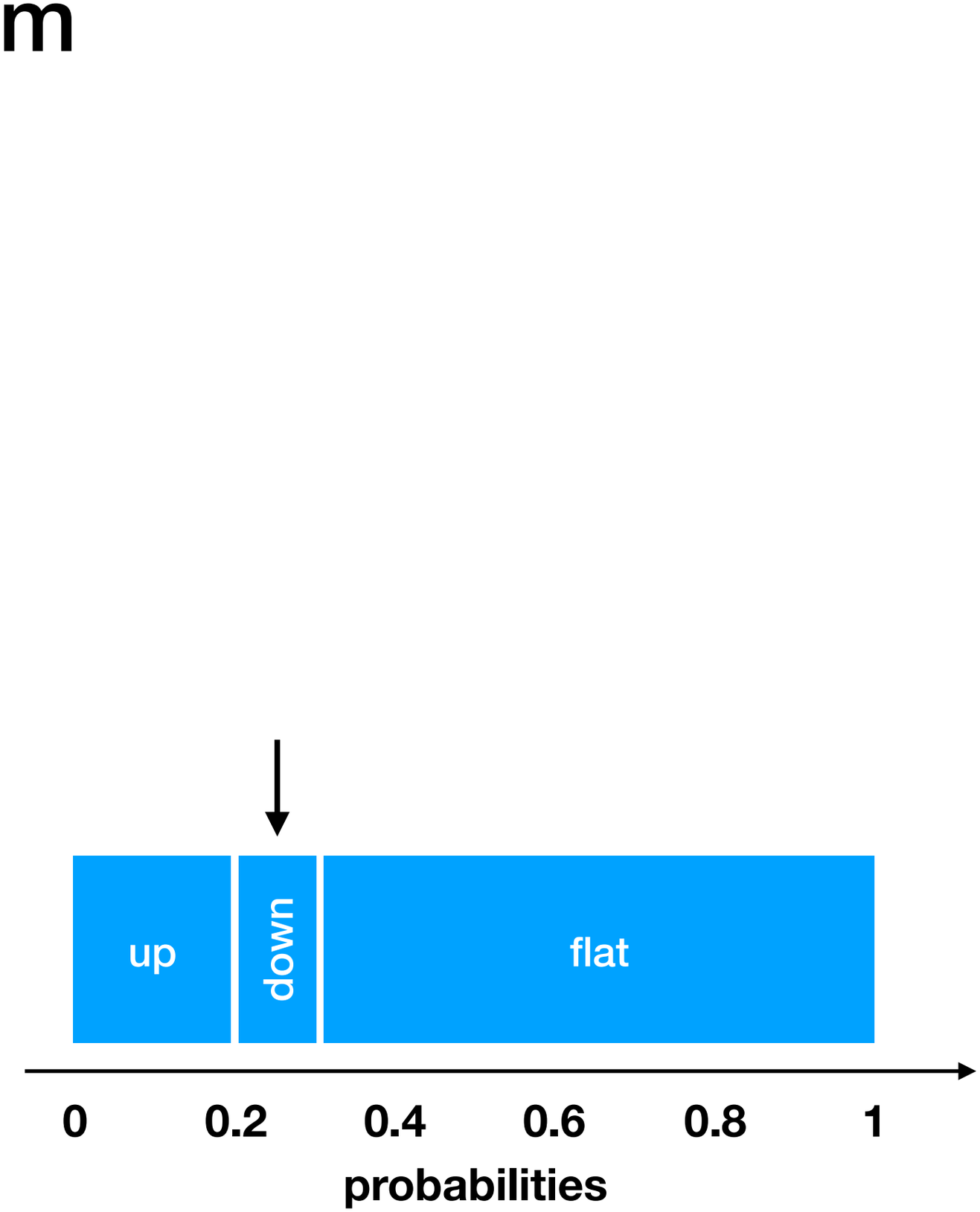

Weighted Random

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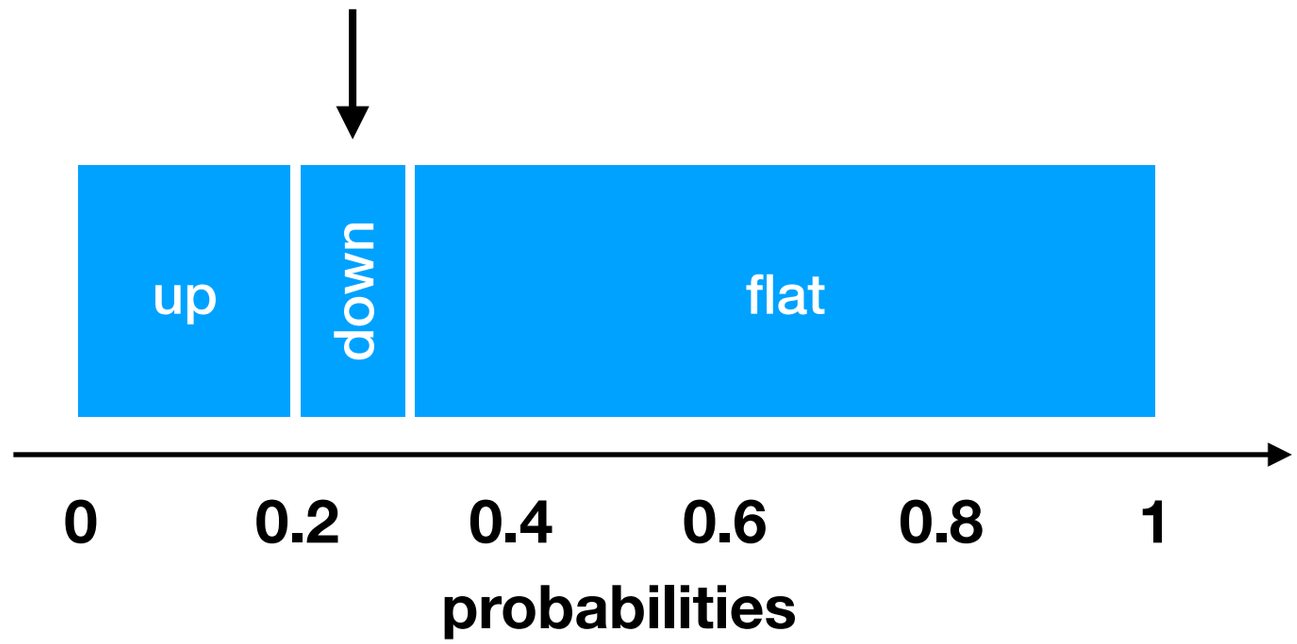
down “wins”



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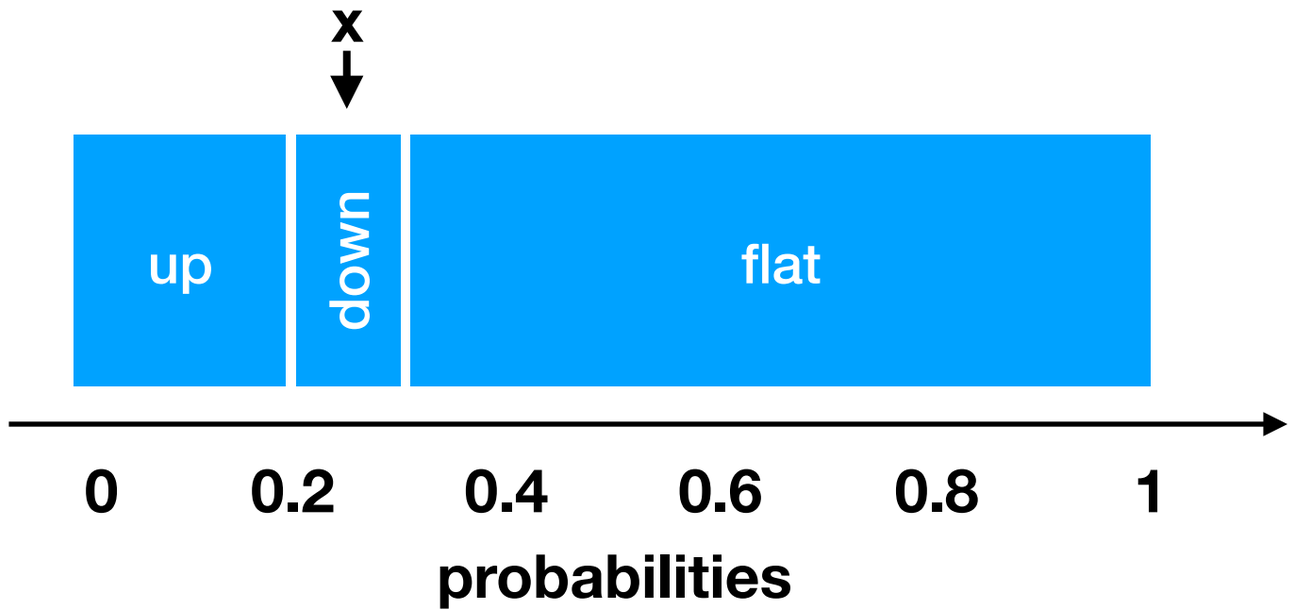


```
end = 0
keys = [“up”, “down”, “flat”]
winner = None
for key in keys:
    end += transitions[key]
    if end >= x:
      winner = key
      break
```

Weighted Random

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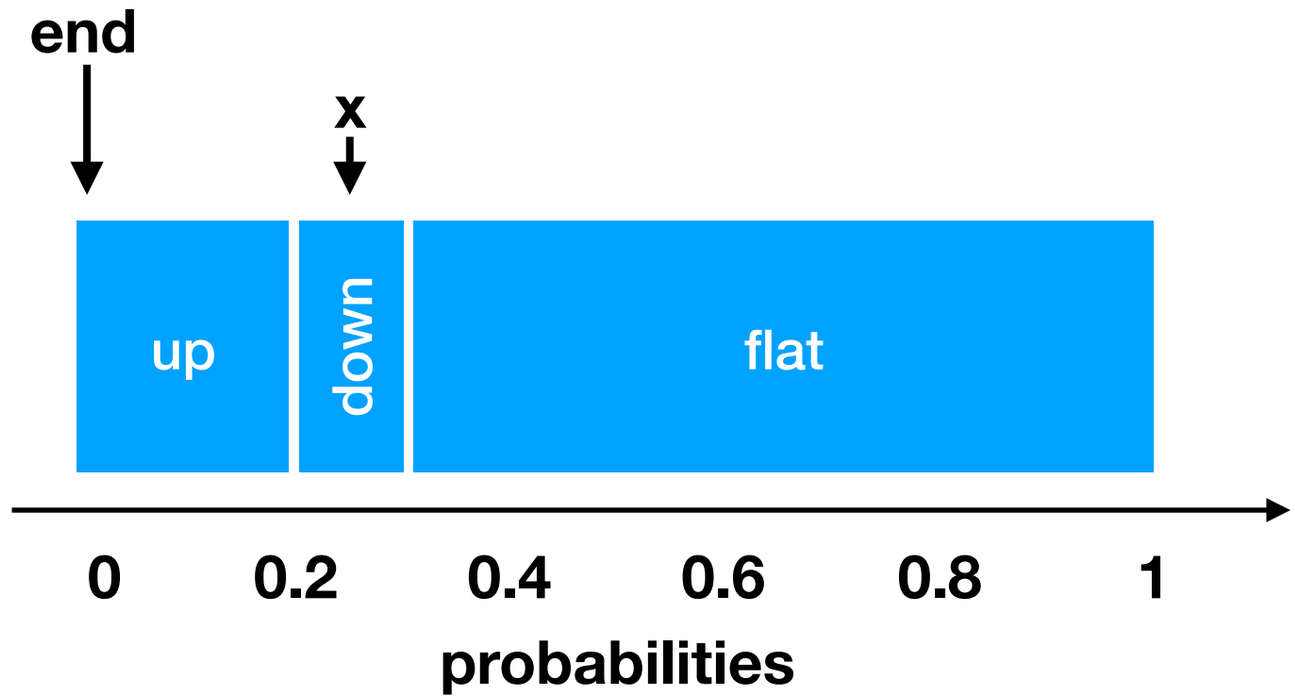


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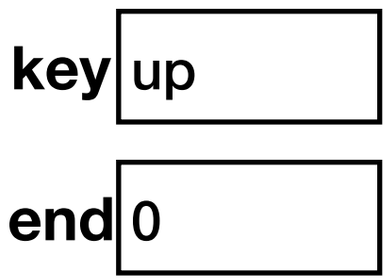

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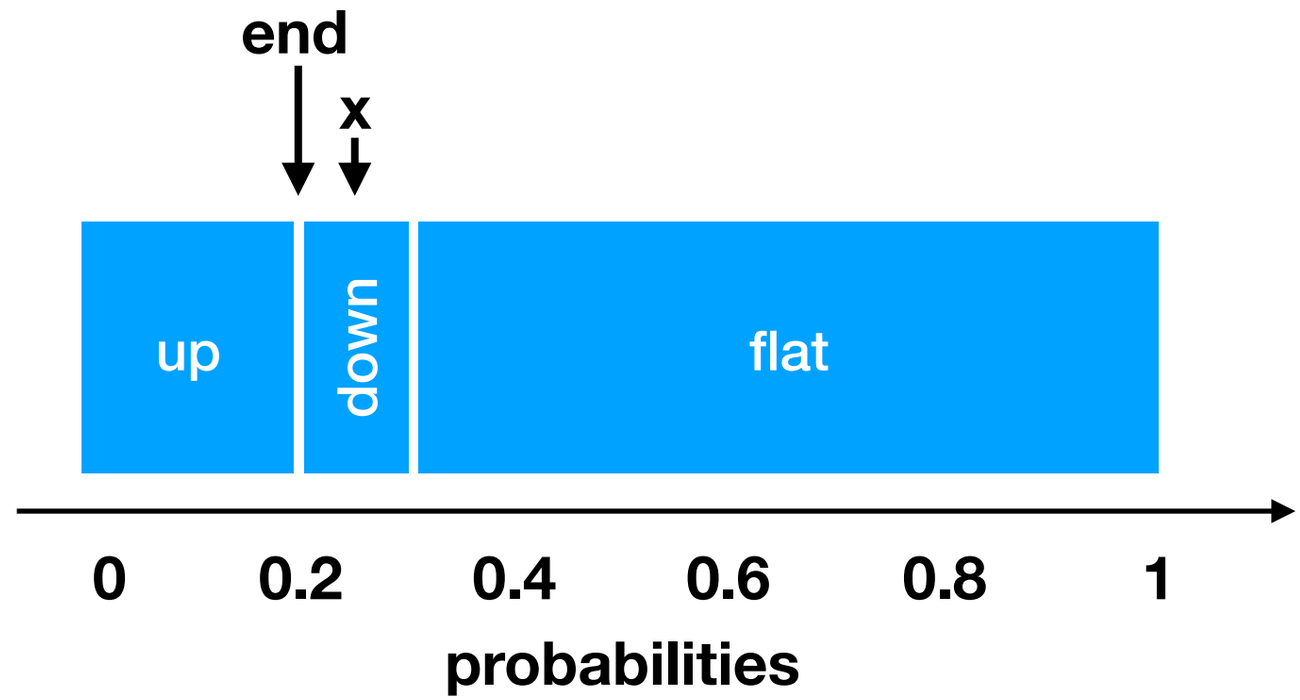


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```

key up

end 0.2

Weighted Random

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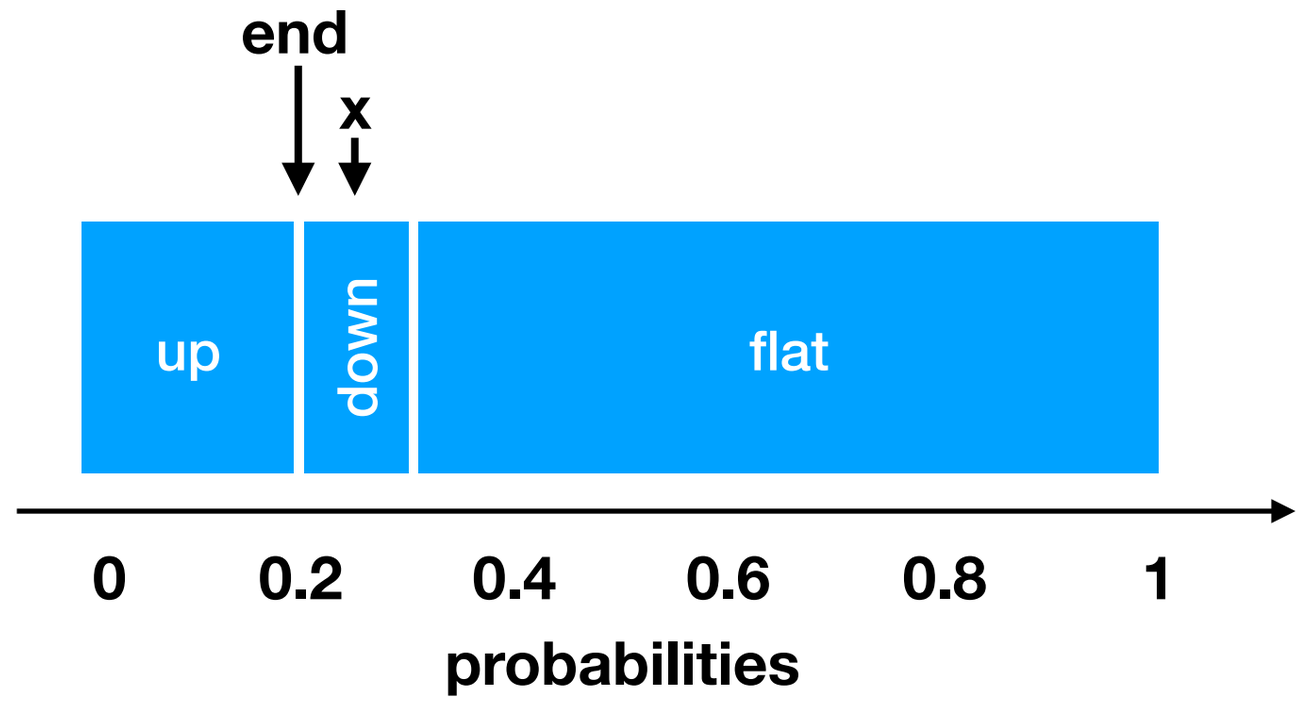


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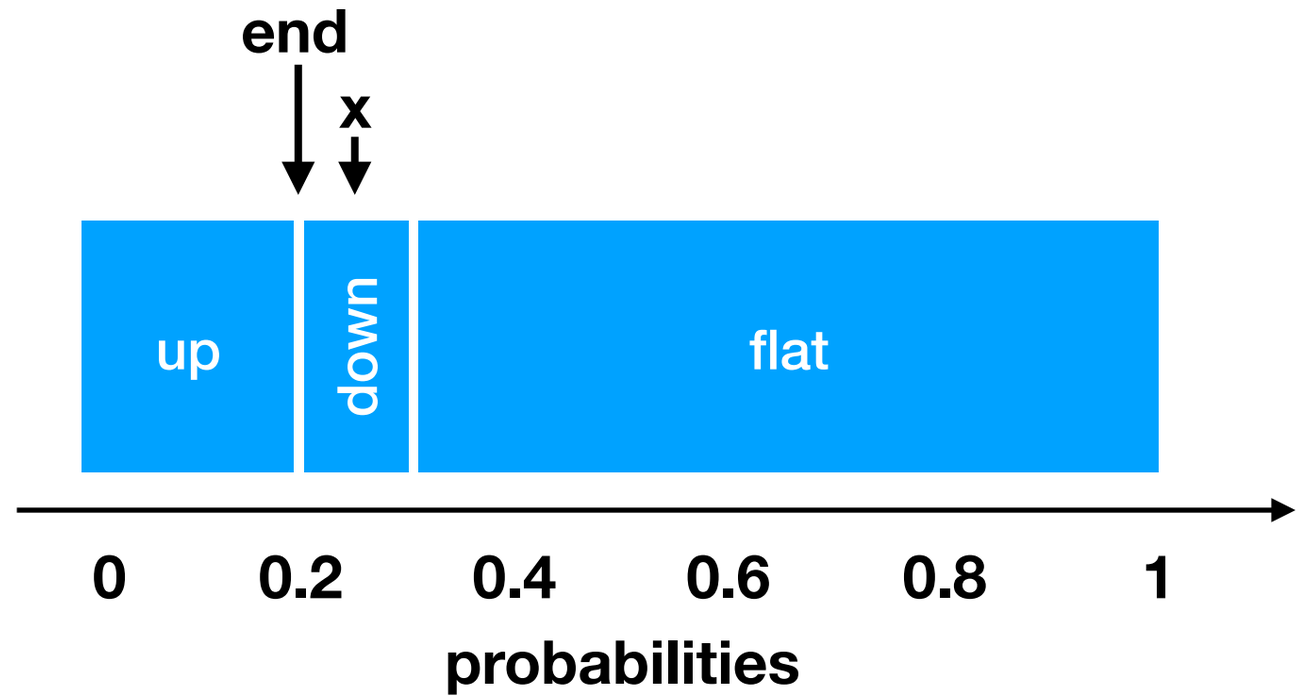


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      break
```

key down

end 0.2

Weighted Random

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}

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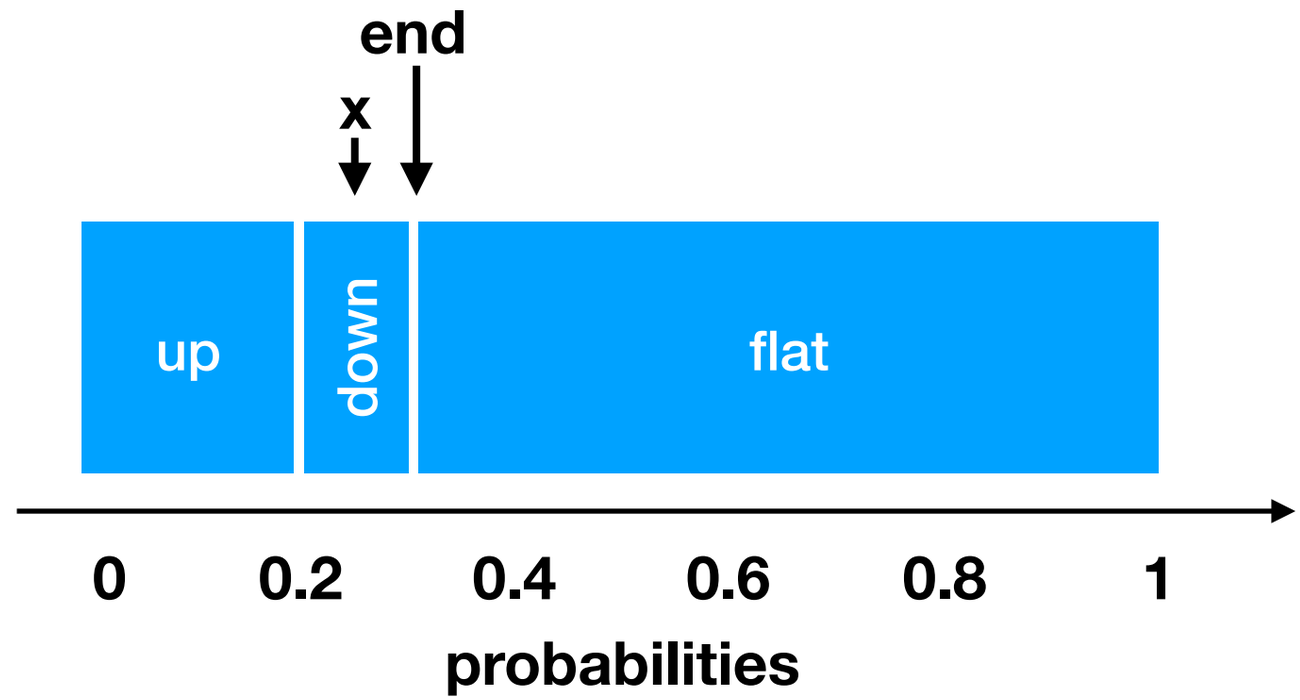



```
end = 0
keys = [“up”, “down”, “flat”]
winner = None
for key in keys:
    end += transitions[key]
    if end >= x:
        winner = key
        break
```

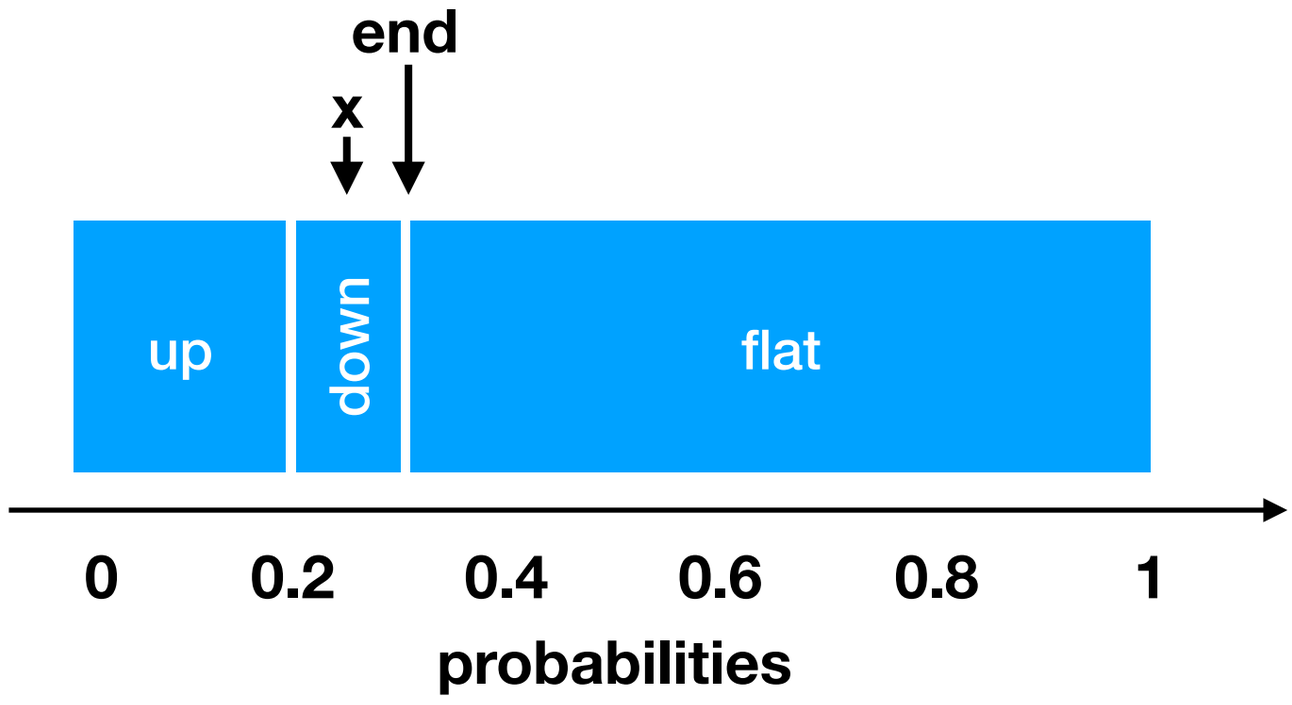
key down

end 0.3

Weighted Random

```
transitions = {
    “up”: 0.2,
    “down”: 0.1,
    “flat”: 0.7
}

x = random.random()
# assume 0.25
```




```
end = 0
keys = [“up”, “down”, “flat”]
winner = None
for key in keys:
    end += transitions[key]
    if end >= x:
        winner = key
        break
```

key down

end 0.3

we randomly chose “down”

Demo 1: Letter Frequency

Goal: if we randomly pick a word in a text, what is the probability that it will be a given letter?

Input:

- Plaintext of book (from Project Gutenberg)

Output:

- The portion of letters in the text that are that letter

Example:

prompt> **python goldbug.py**
text: AAAAABBCCC
A: 50%
B: 20%
C: 30%

Demo 1: Letter Frequency

Goal: if we randomly pick a word in a text, what is the probability that it will be a given letter?

Input:

- Plaintext of book (from Project Gutenberg)

Output:

- The portion of letters in the text that are that letter

Example:

prompt> **python goldbug.py**
text: AAAAABBCCC
A: 50%
B: 20%
C: 30%

Remember: introduce default dictionaries by example!

Today's Outline

More Dictionary Ops

Probabilities Tables

Markov Chains (dict of dict)

Binning (dict of list)

Table Representation (list of dict)

Sequence Data

Consider this sequence: `“the quick tiger is quiet”`

What letter likely comes after “t” in this text?

Sequence Data

Consider this sequence: “**th**e quick **ti**ger is quie**t**”

What letter likely comes after “t” in this text?

Next Letter	Probability
h	50%
i	50%
a	0%
...	0%

Sequence Data

Consider this sequence: “**th**e quick **ti**ger is quie**t**”

What letter likely comes after “t” in this text?

Next Letter	Probability
h	50%
i	50%
a	0%
...	0%

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

Sequence Data

Consider this sequence: “`the quick tiger is quiet`”

What letter likely comes after “t” in this text?

Next Letter	Probability
h	50%
i	50%
a	0%
...	0%

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

What letter likely comes after “q” in this text?

Sequence Data

Consider this sequence: `“the quick tiger is quiet”`

What letter likely comes after “t” in this text?

Next Letter	Probability
h	50%
i	50%
a	0%
...	0%

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

What letter likely comes after “q” in this text?

Next Letter	Probability
u	100%
...	0%

dict for “q”:

```
{“u”: 1.0}
```

Sequence Data

Consider this sequence: “the quick tiger is quiet”

Imagine a next-letter probability dictionary for every letter

What letter likely comes after “t” in this text?

Next Letter	Probability
h	50%
i	50%
a	0%
...	0%

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

What letter likely comes after “q” in this text?

Next Letter	Probability
u	100%
...	0%

dict for “q”:

```
{“u”: 1.0}
```

Sequence Data

Consider this sequence: “the quick brown fox jumped”

What letter likely comes after “t” in this text?

Next Letter	Probability
h	50%
i	50%
a	0%
...	0%

What letter likely comes after “q” in this text?

Next Letter	Probability
u	100%
...	0%

Imagine a next-letter probability dictionary for every letter

dict for “u”:

```
{“i”: 1.0}
```

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

dict for “i”:

```
{“c”: 0.25, “g”: 0.25,
“s”: 0.25, “e”: 0.25}
```

dict for “q”:

```
{“u”: 1.0}
```

...

Sequence Data

Organize all the dicts with a dict:

```
probs = {
  “u”:
}
```

Imagine a next-letter probability dictionary for every letter

dict for “u”:
`{“i”: 1.0}`

dict for “t”:
`{“h”: 0.5, “i”: 0.5}`

dict for “i”:
`{“c”: 0.25, “g”: 0.25, “s”: 0.25, “e”: 0.25}`

dict for “q”:
`{“u”: 1.0}`

...

Sequence Data

Organize all the dicts with a dict:

```
probs = {
   “u”: {“i”: 1.0},

}
```

Imagine a next-letter probability dictionary for every letter

dict for “u”:

```
{“i”: 1.0}
```

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

dict for “i”:

```
{“c”: 0.25, “g”: 0.25,
“s”: 0.25, “e”: 0.25}
```

dict for “q”:

```
{“u”: 1.0}
```

...

Sequence Data

Organize all the dicts with a dict:

```
probs = {
   “u”: {“i”: 1.0},
   “t”: {“h”: 0.5, “i”: 0.5}
   “i”: {“c”: 0.25, “g”: 0.25,
         “s”: 0.25, “e”: 0.25},
   “q”: {“u”: 1.0},
   …
}
```

Imagine a next-letter probability dictionary for every letter

dict for “u”:

```
{“i”: 1.0}
```

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

dict for “i”:

```
{“c”: 0.25, “g”: 0.25,
“s”: 0.25, “e”: 0.25}
```

dict for “q”:

```
{“u”: 1.0}
```

▪▪▪

Sequence Data

Organize all the dicts with a dict:

```
probs = {
   “u”: {“i”: 1.0},
   “t”: {“h”: 0.5, “i”: 0.5}
   “i”: {“c”: 0.25, “g”: 0.25,
         “s”: 0.25, “e”: 0.25},
   “q”: {“u”: 1.0},
   …
}
```

```
probs[“i”]
```

Imagine a next-letter probability dictionary for every letter

dict for “u”:

```
{“i”: 1.0}
```

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

dict for “i”:

```
{“c”: 0.25, “g”: 0.25,
“s”: 0.25, “e”: 0.25}
```

dict for “q”:

```
{“u”: 1.0}
```

▪▪▪

Sequence Data

Organize all the dicts with a dict:

```
probs = {
   “u”: {“i”: 1.0},
   “t”: {“h”: 0.5, “i”: 0.5}
   “i”: {“c”: 0.25, “g”: 0.25,
         “s”: 0.25, “e”: 0.25},
   “q”: {“u”: 1.0},
   …
}
```

probs[“i”][“e”] ➡ 0.25

There is a 25% probability that the letter following an “i” is an “e”

Imagine a next-letter probability dictionary for every letter

dict for “u”:

```
{“i”: 1.0}
```

dict for “t”:

```
{“h”: 0.5, “i”: 0.5}
```

dict for “i”:

```
{“c”: 0.25, “g”: 0.25,
“s”: 0.25, “e”: 0.25}
```

dict for “q”:

```
{“u”: 1.0}
```

▪▪▪

Vocabulary

```
probs = {
   "u": {"i": 1.0},
   "t": {"h": 0.5, "i": 0.5}
   "i": {"c": 0.25, "g": 0.25,
         "s": 0.25, "e": 0.25},
   "q": {"u": 1.0},
   …
}
```

The collection of transition probabilities like this is sometimes called a "stochastic matrix"

Processes that make probabilistic transitions like this (e.g., from one letter to the next) are called "Markov chains"

Random Text Generation

all letters equally likely

XFOML RXKHRJFFJUJ
ZLPWCFWKCYJ FFJEYVKCQSGHYD
QPAAMKBZAACIBZLHJQD.

weighted random, based on frequency in a text
(implement with dict)

OCRO HLI RGWR NMIELWIS EU LL
NBNESEBYA TH EEI ALHENHTTPA
OOBTTVA NAH BRL.

probability of each letter based on previous letter
(implement with dict of dicts)

ON IE ANTSOUTINYS ARE T
INCTORE ST BE S DEAMY ACHIN D
ILONASIVE TUCOOWE AT
TEASONARE FUSO TIZIN ANDY
TOBE SEACE CTISBE.

Examples from *A Mind at Play*, by Soni and Goodman

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ILONASIVE TUCOOWE AT
TEASONARE FUSO TIZIN ANDY
TOBE SEACE CTISBE.

Examples from *A Mind at Play*, by Soni and Goodman

Demo 2: Conditional Letter Frequency

Goal: if we look at given letter,
what is the next letter likely to be

Input:

- Plaintext of book (from Project Gutenberg)

Output:

- Transition probabilities
- Randomly generated text, based on probabilities

Today's Outline

More Dictionary Ops

Probabilities Tables

Markov Chains (dict of dict)

Binning (dict of list)

Table Representation (list of dict)

Binning

Often, we want to break input data into categories called “buckets” or “bins”, then do stats (e.g., median) on each bucket

all data

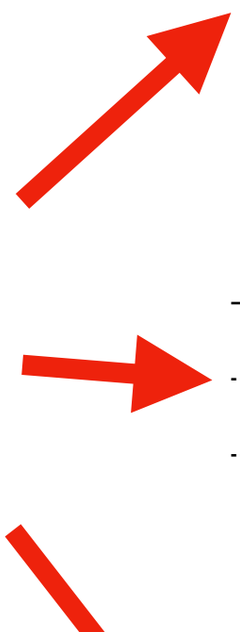
Year	ID	Speed
2014	A	123
2015	B	120
2015	C	140
2016	D	100
2015	E	130
2016	F	200

Binning

Often, we want to break input data into categories called "buckets" or "bins", then do stats (e.g., median) on each bucket

all data

Year	ID	Speed
2014	A	123
2015	B	120
2015	C	140
2016	D	100
2015	E	130
2016	F	200



bin for 2014

Year	ID	Speed
2014	A	123

bin for 2015

Year	ID	Speed
2015	B	120
2015	C	140
2015	E	130

bin for 2016

Year	ID	Speed
2016	D	100
2016	F	200

Binning

Often, we want to break input data into categories called "buckets" or "bins", then do stats (e.g., median) on each bucket

all data

Year	ID	Speed
2014	A	123
2015	B	120
2015	C	140
2016	D	100
2015	E	130
2016	F	200

bin for 2014

Year	ID	Speed
2014	A	123

→ ?

bin for 2015

Year	ID	Speed
2015	B	120
2015	C	140
2015	E	130

→ 130 (median)

bin for 2016

Year	ID	Speed
2016	D	100
2016	F	200

→ ?

Binning

Often, we want to break input data into categories called "buckets" or "bins", then do stats (e.g., median) on each bucket

all data

Year	ID	Speed
2014	A	123
2015	B	120
2015	C	140
2016	D	100
2015	E	130
2016	F	200

bin for 2014

Year	ID	Speed
2014	A	123

123 (median)

bin for 2015

Year	ID	Speed
2015	B	120
2015	C	140
2015	E	130

130 (median)

bin for 2016

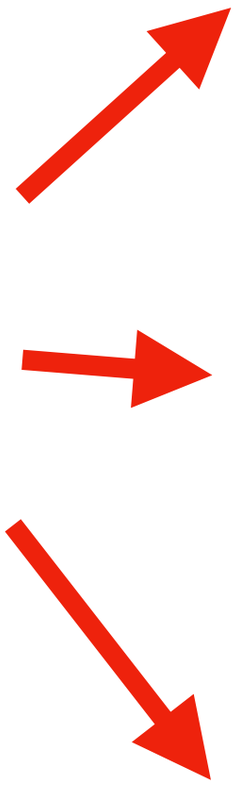
Year	ID	Speed
2016	D	100
2016	F	200

150 (median)

Bins with lists and dicts

all data

```
rows = [
    [2014, “A”, 123],
    [2015, “B”, 120],
    [2015, “C”, 140],
    [2016, “D”, 100],
    [2015, “E”, 130],
    [2016, “F”, 200],
]
```



bin for 2014

```
bin2014 = [
    [2014, “A”, 123],
]
```

bin for 2015

```
bin2015 = [
    [2015, “B”, 120],
    [2015, “C”, 140],
    [2015, “E”, 130],
]
```

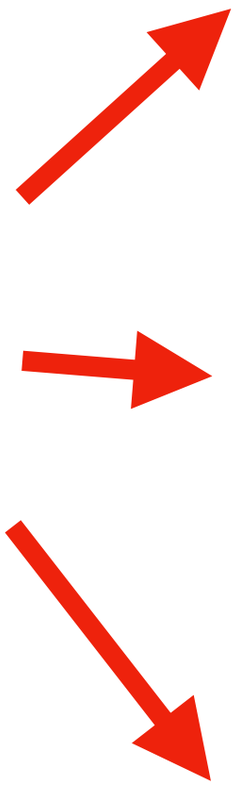
bin for 2016

```
bin2016 = [
    [2016, “D”, 100],
    [2016, “F”, 200],
]
```

Bins with lists and dicts

all data

```
rows = [
    [2014, “A”, 123],
    [2015, “B”, 120],
    [2015, “C”, 140],
    [2016, “D”, 100],
    [2015, “E”, 130],
    [2016, “F”, 200],
]
```



bin for 2014

```
bin2014 = [
    [2014, “A”, 123],
]
```

bin for 2015

```
bin2015 = [
    [2015, “B”, 120],
    [2015, “C”, 140],
    [2015, “E”, 130],
]
```

bin for 2016

```
bin2016 = [
    [2016, “D”, 100],
    [2016, “F”, 200],
]
```

how to keep track of all the lists?

Bins with lists and dicts

all data

```
rows = [
    [2014, “A”, 123],
    [2015, “B”, 120],
    [2015, “C”, 140],
    [2016, “D”, 100],
    [2015, “E”, 130],
    [2016, “F”, 200],
]
```

```
bins = {
    2014: [
        [2014, “A”, 123],
    ],
    2015: [
        [2015, “B”, 120],
        [2015, “C”, 140],
        [2015, “E”, 130],
    ],
    2016: [
        [2016, “D”, 100],
        [2016, “F”, 200],
    ]
}
```

Bins with lists and dicts

all data

```
rows = [
    [2014, “A”, 123],
    [2015, “B”, 120],
    [2015, “C”, 140],
    [2016, “D”, 100],
    [2015, “E”, 130],
    [2016, “F”, 200],
]
```

```
bins = {
    2014: [
        [2014, “A”, 123],
    ],
    2015: [
        [2015, “B”, 120],
        [2015, “C”, 140],
        [2015, “E”, 130],
    ],
    2016: [
        [2016, “D”, 100],
        [2016, “F”, 200],
    ]
}
```

Demo 3: Median Tornado Speed per Year

Goal: modify tornado.py (last lecture)
to print median speed of tornados for each year

Input:

- Tornado CSV

Output:

- Median within each year

Example:

prompt> **python tornados.py**
...
2015: 130
2016: 123
2017: 90

Today's Outline

More Dictionary Ops

Probabilities Tables

Markov Chains (dict of dict)

Binning (dict of list)

Table Representation (list of dict)

Table Representation

name	x	y
Alice	30	20
Bob	5	11
Cindy	-2	50

list of list representation

```
header = [“name”, “x”, “y”]
rows = [
    [“Alice”, 30, 20],
    [“Bob”,   5,  11],
    [“Cindy”, -2, 50],
]
```

Table Representation

name	x	y
Alice	30	20
Bob	5	11
Cindy	-2	50

list of list representation

```
header = [“name”, “x”, “y”]
rows = [
    [“Alice”, 30, 20],
    [“Bob”,   5,  11],
    [“Cindy”, -2, 50],
]
```

list of dict representation

```
[
  {“name”:“Alice”, “x”:30, “y”:20”},
  {“name”:“Bob”,   “x”:5,  “y”:11”},
  {“name”:“Cindy”, “x”:-2, “y”:50”},
]
```

Table Representation

name	x	y
Alice	30	20
Bob	5	11
Cindy	-2	50

list of list representation

```
header = [“name”, “x”, “y”]
rows = [
    [“Alice”, 30, 20],
    [“Bob”,   5,  11],
    [“Cindy”, -2, 50],
]
```

list of dict representation

```
[
  {“name”:“Alice”, “x”:30, “y”:20”},
  {“name”:“Bob”,   “x”:5,  “y”:11”},
  {“name”:“Cindy”, “x”:-2, “y”:50”},
]
```

Table Representation

name	x	y
Alice	30	20
Bob	5	11
Cindy	-2	50

list of list representation

```
header = [“name”, “x”, “y”]
rows = [
    [“Alice”, 30, 20],
    [“Bob”,   5,  11],
    [“Cindy”, -2, 50],
]
```

rows[2][header.index(“y”)]

list of dict representation

```
[
  {“name”:“Alice”, “x”:30, “y”:20”},
  {“name”:“Bob”,   “x”:5,  “y”:11”},
  {“name”:“Cindy”, “x”:-2, “y”:50”},
]
```

Table Representation

name	x	y
Alice	30	20
Bob	5	11
Cindy	-2	50

list of list representation

```
header = [“name”, “x”, “y”]
rows = [
    [“Alice”, 30, 20],
    [“Bob”,   5,  11],
    [“Cindy”, -2, 50],
]
```

rows[2][header.index(“y”)]

list of dict representation

```
[
  {“name”:“Alice”, “x”:30, “y”:20”},
  {“name”:“Bob”,   “x”:5,  “y”:11”},
  {“name”:“Cindy”, “x”:-2, “y”:50”},
]
```

rows[2][“y”]

Demo 4: Table Transform

Goal: create function that transforms list of lists table
to a list of dicts table

Input:

- List of lists (from a CSV)

Output:

- List of dicts

Example:

```
>>> header = [“x”,”y”]
>>> rows = [[1,2], [3,4]]
>>> transform(header, rows)
[{“x”:1, “y”:2}, {“x”:3, “y”:4}]
```