

# Social Data Science: Machine Learning & Econometrics

Exercise class 2

February 21, 2020

# Today's quick warmup

**Q:** Write a *generator* `pascal()` that *yields* subsequent rows in Pascal's Triangle.

row 1				1			
row 2			1		1		
row 3		1		2		1	
row 4	1		3		3		1
⋮							

Your generator should take 0 arguments, `next()` should give you the next row in the triangle.

**Bonus:** Sierpiński's triangle can be drawn by plotting only the odd numbers of pascal's triangle as black dots. Do this for  $n = 1024^1$  rows of pascal's triangle.

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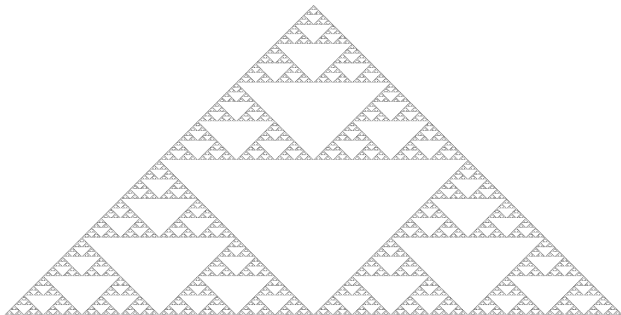
<sup>1</sup>Some of you might need to think about the maximum size of integers to get  $n$  above 50-60

# Today's quick warmup - solution

Yield the first row [1] manually, then forever pad the last row with 0's and yield the next row.

```
def pascals():  
    row = [1]  
    yield row  
    while True:  
        row = [0] + row + [0]  
        row = [i+j for i,j in zip(row[:-1], row[1:])]   
        yield row
```

# Today's quick warmup - bonus solution



# Today's quick warmup - bonus solution

Make a big 0-matrix and fill in as we go.

```
import numpy as np
import matplotlib.pyplot as plt

def plot_sierpinski(n):
    M = np.zeros(shape = (n, 2*n))
    midpoint = int(np.ceil(2*n / 2))
    triangle = pascals()

    for row in range(n):
        elems = np.array([t%2!=0 for t in next(triangle)])
        insert = np.insert(elems, range(1,row+1) ,0)
        M[row, midpoint-row:midpoint+row+1] = insert
    return M

M = plot_sierpinski(1000)
plt.imshow(M)
```

# Last lecture in a nutshell

Once again lots of stuff was covered in the lecture

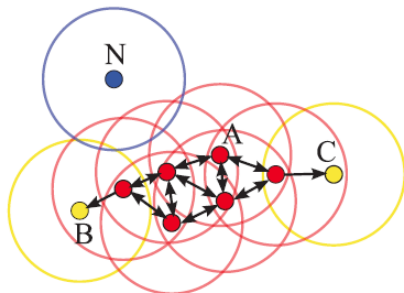
- ▶ **Dimensionality reduction:** PCA, LDA, t-SNE and UMAP
- ▶ **Clustering:** K-means, C-means, Mixture models, ..., DBSCAN
- ▶ **PCA:** Reduce dimensionality by projecting on “variance explaining” basis.
- ▶ Caveats: finds best *global linear* projection.
- ▶ **LDA:** Similar to PCA, but use information on class labels to target *maximum class separation*.

```
# Import Pipeline, PCA
# and StandardScaler
k = 10
model = Pipeline([
    ('scale', StandardScaler()),
    ('pca', PCA(n_components=k))
])

model.fit_transform(X)
```

## Last lecture in a nutshell

**DBSCAN:** independently sets the number of clusters, fits weird-shaped clusters and allows for noise observations.



- ▶ *Caveats:* non-deterministic, uses (by default) Euclidian distance, so suffers from curse of dimensionality, has a fixed  $\epsilon$ , so clusters of different density cause problems.
- ▶ Note also that the combination of Euclidian distances and fixed  $\epsilon$  requires common scale to be meaningful.