



# ECON526: Quantitative Economics with Data Science Applications

*Linear and Nonlinear Dynamics*

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# Overview

# Motivation and Materials

- In this lecture, we will apply some of our tools to non-linear equations, which come up in macroeconomics, industrial organization, and econometrics
- The primary example is a simple version of the growth models
- We will introduce the idea of a fixed point, which has many applications across fields of economics
- A special emphasis will be placed on analyzing stability - which connects to the eigenvalues of the dynamical system

# Packages and Other Materials

- Some additional material and references
  - Solow-Swan Model
  - Dynamics and Stability in One Dimension

```
1 import matplotlib.pyplot as plt
2 import numpy as np
3 from numpy.linalg import norm
4 from scipy.linalg import inv, solve, det, eig, lu, eigvals
```



# Fixed Points

# Fixed Points of a Map

## Fixed Point

Let  $f : S \rightarrow S$  where we will assume  $S \subseteq \mathbb{R}^N$ . Then a fixed point  $x^* \in S$  of  $f$  is one where

$$x^* = f(x^*)$$

Fixed points **may not exist**, or could have **multiplicity**

# Fixed Points for Linear Functions

- We have already done this for linear functions.
- Let  $f(x) = \begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix} x$
- Then we know that  $x^* = \begin{bmatrix} 0 & 0 \end{bmatrix}^T$  is a fixed point
- Are there non-trivial others?
  - Could check eigenvectors as we did before,  $\lambda \times x = Ax$
  - If there is an  $(\lambda, x)$  pair with  $\lambda = 1$  it is a fixed point

```
1 A = np.array([[0.8, 0.2], [0.2, 0.8]])
2 eigvals, eigvecs = eig(A)
3 print(f"lambda_1={eigvals[0]}, ||x* - A x*||={norm(A @ eigvecs[:,0] - eigvecs[:,0])}")
```

```
lambda_1=(1+0j), ||x* - A x*||=1.1102230246251565e-16
```

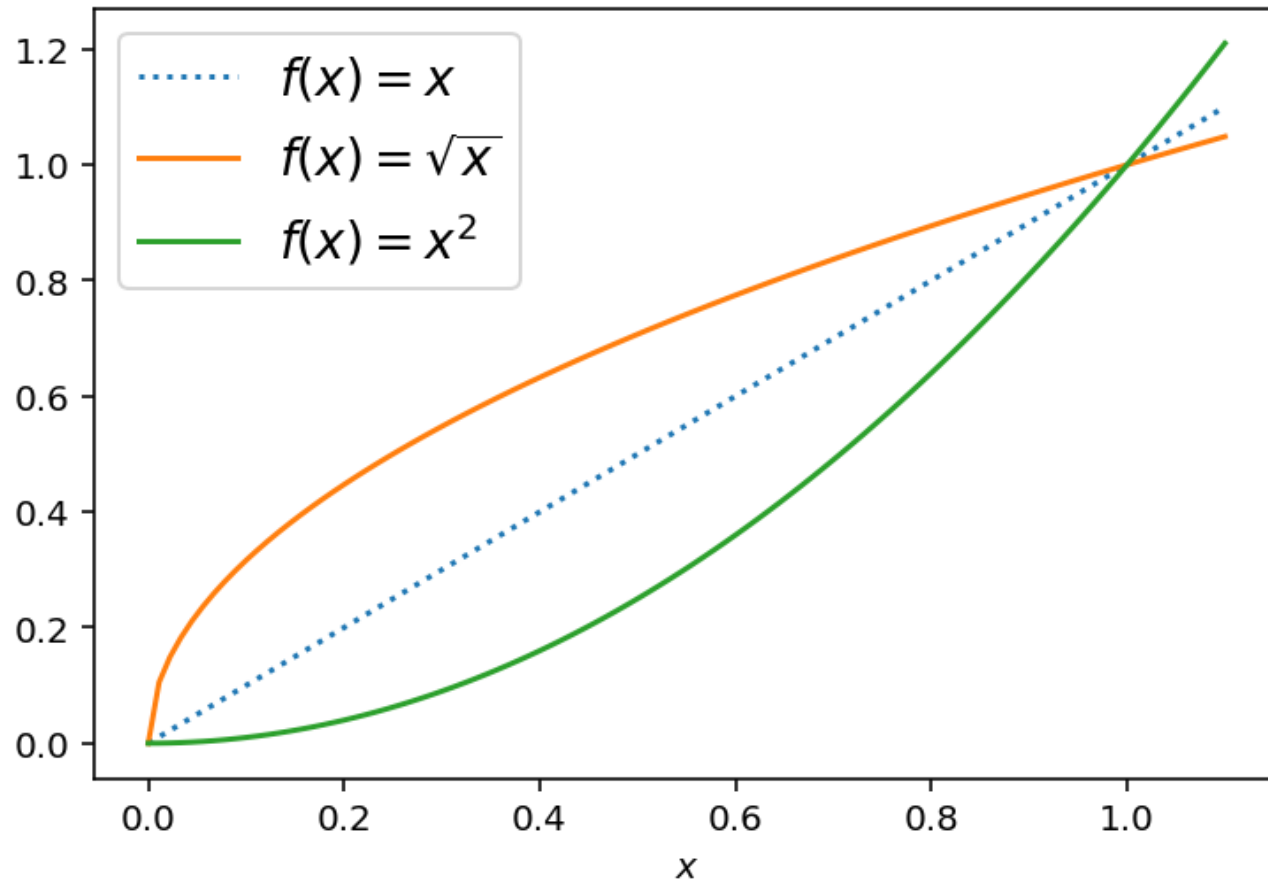


# Fixed Points for Nonlinear Functions

- Consider  $f(x) = \sqrt{x}$  and  $f(x) = x^2$  for  $x \geq 0$
- Trivially  $x^* = 0$  is a fixed point of both, but what about others?
- Plot the 45-degree line to see if they cross! Seems  $x^* = 1$  as well?
  - As we will discuss, though. The shape at  $x^* = 1$  and  $x^* = 0$  is very different
  - Think about what happens if we “perturb” slightly away from that point?

# Plot Against 45 degree line

- Consider  $f(x) = \sqrt{x}$  and  $f(x) = x^2$  for  $x \geq 0$

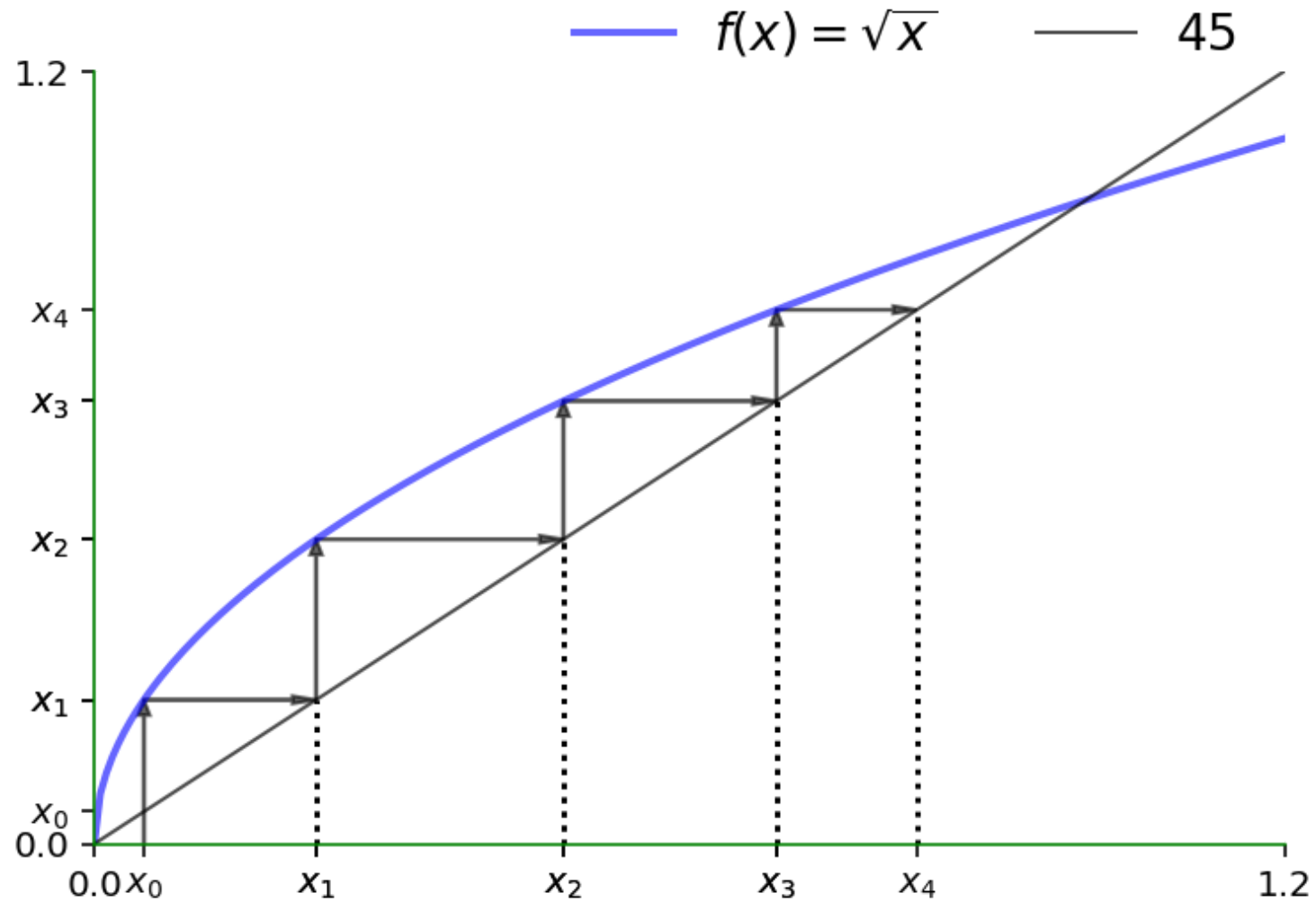


# Interpreting Iterations with the 45 degree line

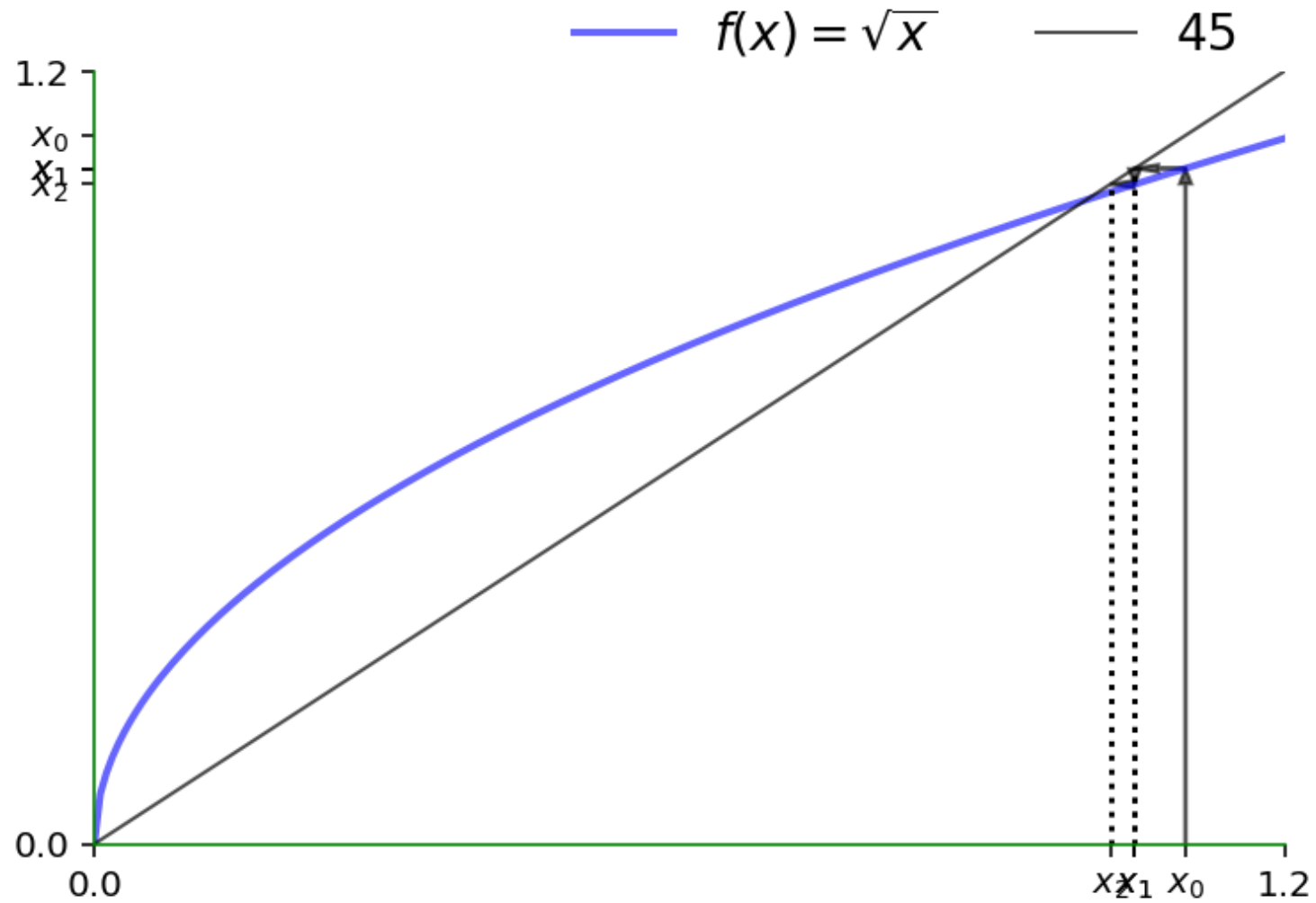
- To use these figures:
  1. Start with any point on the x-axis
  2. Jump to the  $f(\cdot)$  for that point to see where it went
  3. Go across to the 45 degree line
  4. Then down to the new value
- Repeat! Useful to interpret dynamics as well as various numerical methods
- Gives intuition on speed of convergence/etc. as well

See [QuantEcon Scalar dynamics](#) for base code

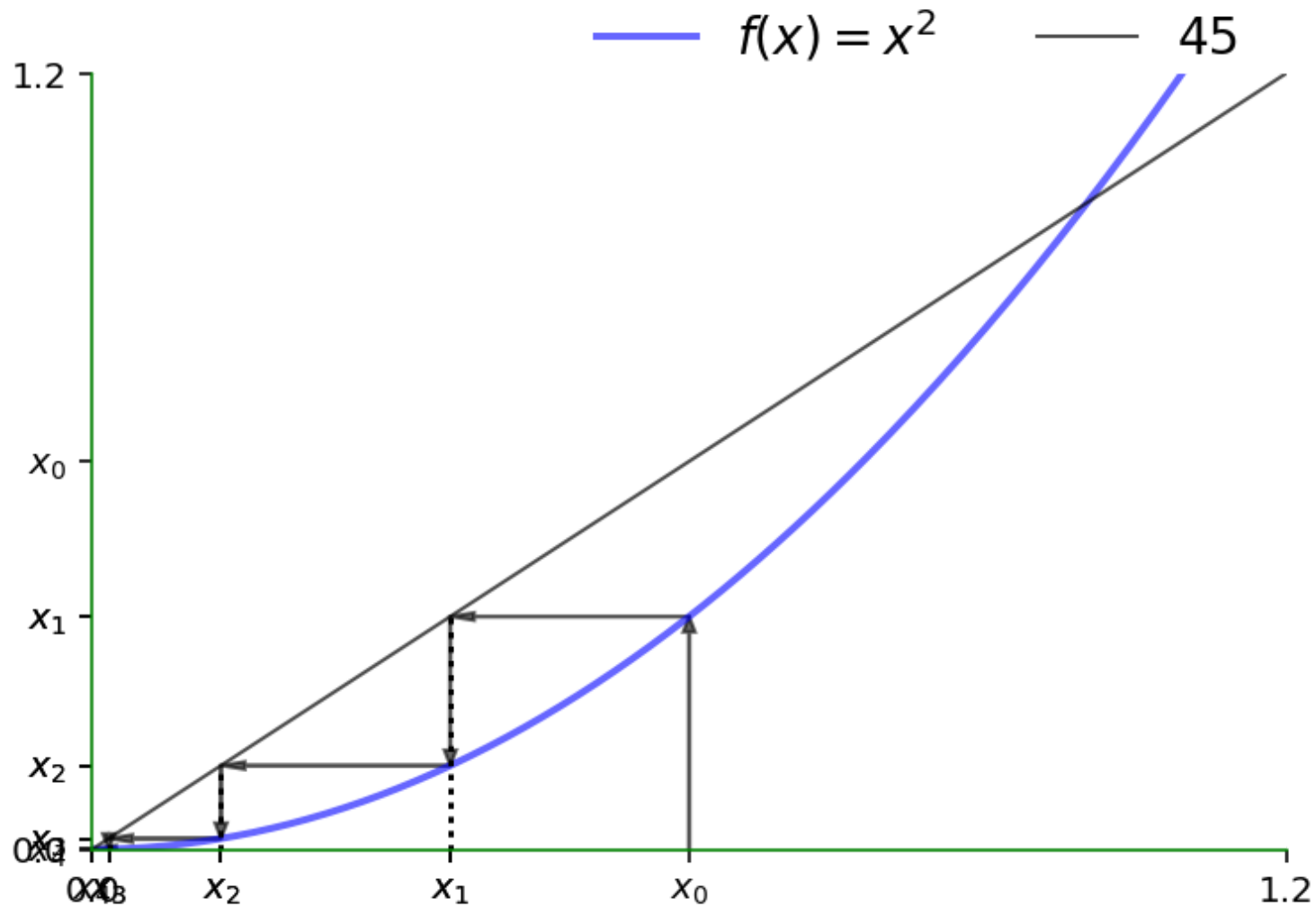
Evaluating the  $\sqrt{x}$  near  $x = 0.05 > 0$



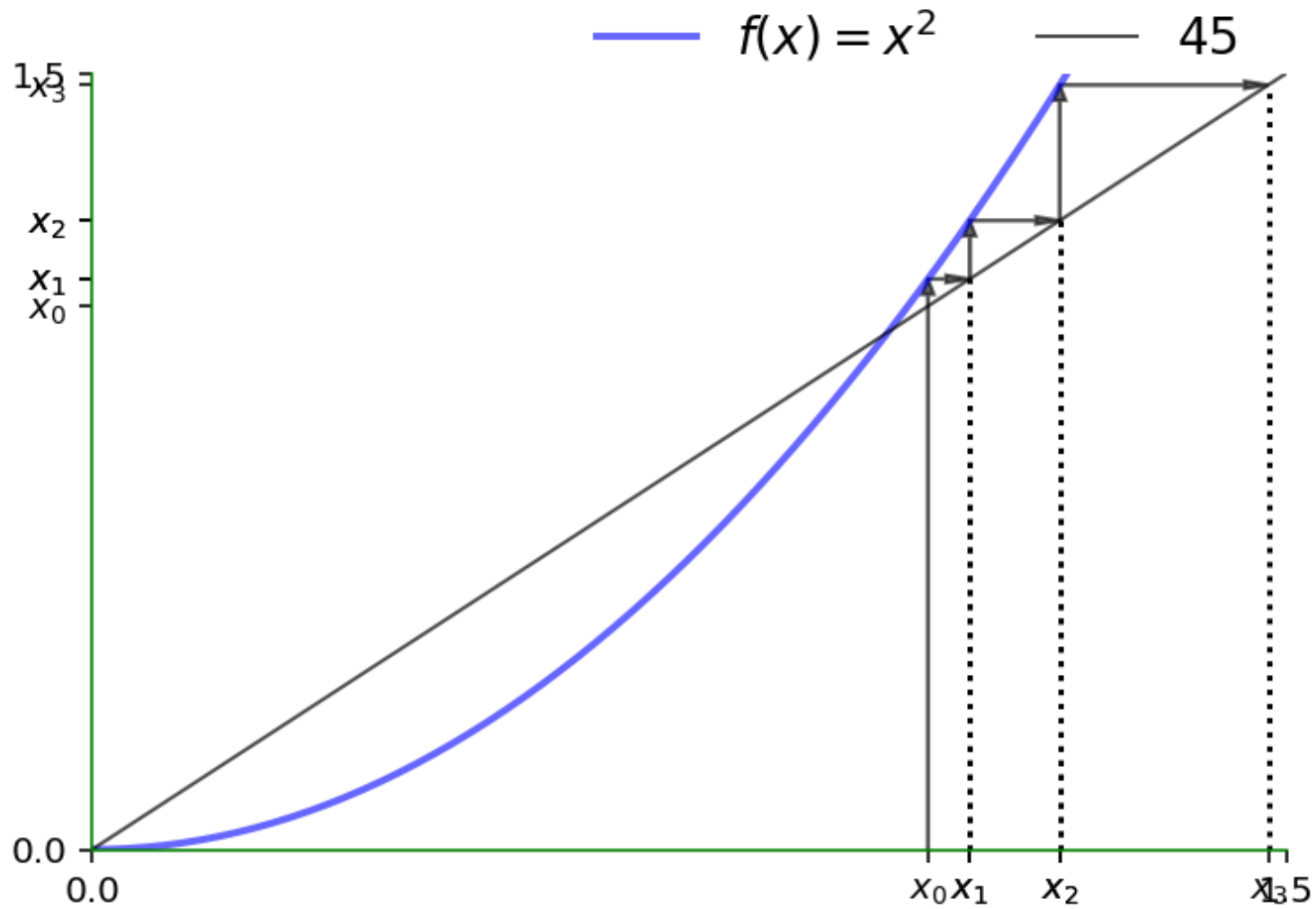
Evaluating the  $\sqrt{x}$  near  $x = 1.1 > 1$



# Evaluating the $x^2$ for $x = 0.6 < 1$



# Evaluating the $x^2$ for $x = 1.01 > 1$





# Linear Dynamics and Stability



# Scalar Linear Model

$$x_{t+1} = ax_t + b \equiv f(x_t), \quad \text{given } x_0$$

$$x_1 = ax_0 + b$$

$$x_2 = ax_1 + b = a^2x_0 + ab + b$$

...

$$x_t = a^t x_0 + b \sum_{i=0}^{t-1} a^i = a^t x_0 + b \frac{1 - a^t}{1 - a}$$

$$x^* \equiv \lim_{t \rightarrow \infty} x_t = \begin{cases} \frac{b}{1-a} & \text{if } |a| < 1 \\ \text{diverges} & \text{if } |a| \geq 1 \\ \text{indeterminate} & \text{if } a = 1 \end{cases}$$

# Stability and Jacobians

- Given  $f(x_t) = ax_t + b$ 
  - The Jacobian (derivative since scalar)  $\nabla f(x_t) = a$
- Eigenvalues of a scalar are just the value itself, so can write the condition as
  - Stable at fixed point  $x^*$  if  $\rho(\nabla f(x^*)) < 1$ , where  $\rho(A) = \max_i |\lambda_i(A)|$  the spectral radius
  - Saw this as a condition for stability with higher-dimensional linear systems when looking at Present Discounted Values

# Linearization and Stability

- Important condition for stability with nonlinear  $f(\cdot)$
- Intuition: assume  $x^*$  exists and then
  - Linearize around the steady state and see if it would be locally explosive
  - Necessary but not sufficient.  $\rho(\nabla f(x^*)) > 1 \implies x^*$  can't be a stable fixed point
- You may see this when working with macro models in Dynare and similar methods in macroeconomics

# Linearization

- Assume steady state  $x^* = f(x^*)$  exists, with system  $x_{t+1} = f(x_t)$
- Take **first-order taylor expansion** around  $x^*$

$$x_{t+1} = f(x^*) + \nabla f(x^*)(x_t - x^*) + \text{second order and smaller terms}$$

$$x_{t+1} - x^* \approx \nabla f(x^*)(x_t - x^*)$$

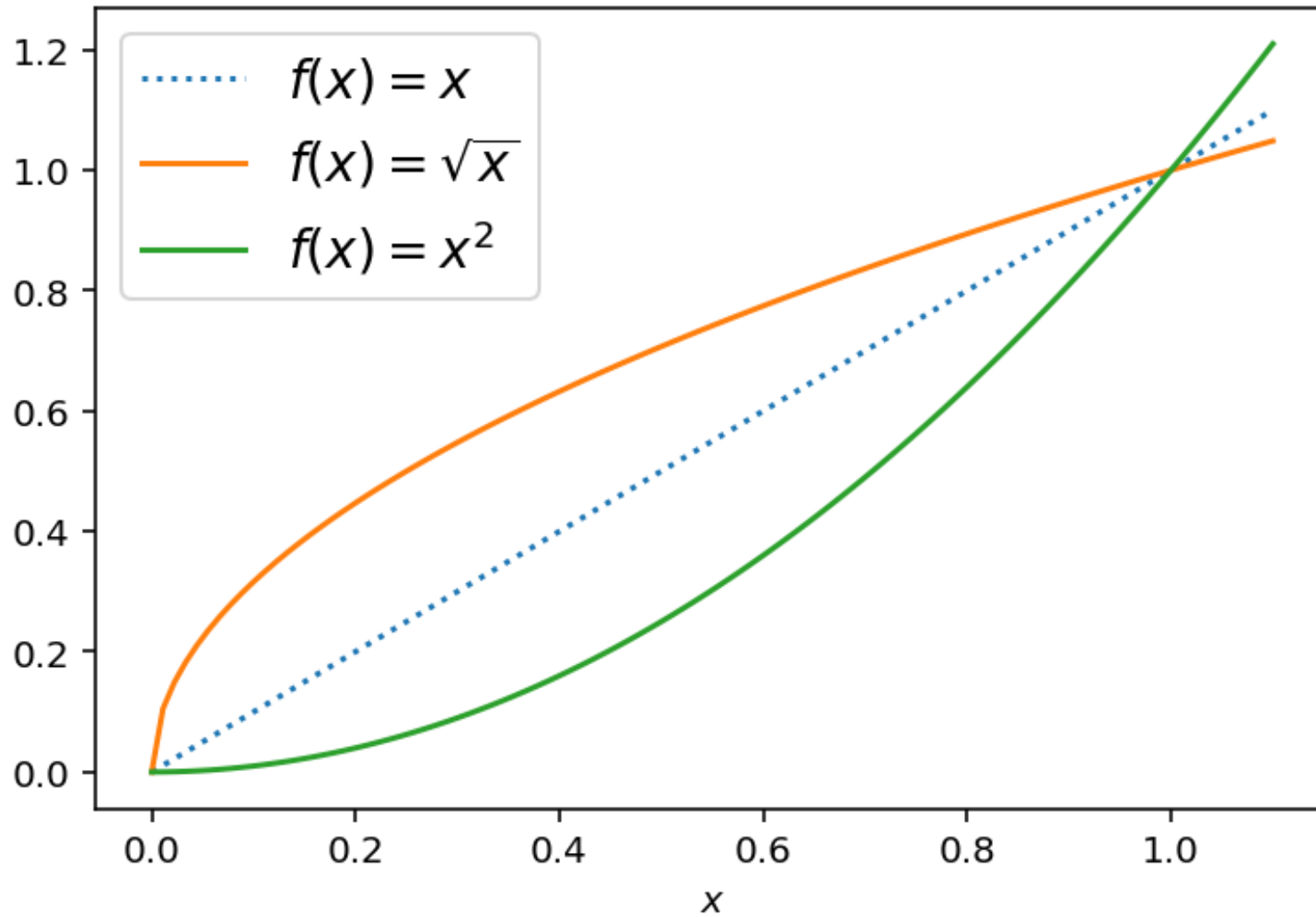
$$\hat{x}_{t+1} \approx \nabla f(x^*)\hat{x}_t$$

- Where the last formulation is common in macroeconomics and time-series econometrics.  $\hat{x}_t \equiv x_t - x^*$  is the **deviation from the steady state**
  - For the linear case, these would all be exact as there are no higher-order terms

# Quality of Linearization

- Gives approximate dynamics for a perturbation close to the steady state
  - May have good approximation far away from  $x^*$  if  $f(\cdot)$  is close to linear
  - May have terrible approximations close to  $x^*$  if  $f(\cdot)$  highly nonlinear/asymmetric
  - Often [log-linearization](#) is used instead, which expresses in percent deviation

# Plot Against 45 degree line Reminder



# Stability of $\sqrt{x}$ and $x^2$

- Recall that both had fixed points at  $x^* = 0$  and  $x^* = 1$
- Lets check derivatives! Let  $f_1(x) = \sqrt{x}$  and  $f_2(x) = x^2$ 
  - $\nabla f_1 x = \frac{1}{2\sqrt{x}}$  and  $\nabla f_2(x) = 2x$
- Check spectral radius of the Jacobians (trivial since univariate) at the fixed points:
  - At  $x^* = 0$ ,  $\nabla f_1(0) = \infty$  and  $\nabla f_2(0) = 0$
  - At  $x^* = 1$ , find  $\nabla f_1(1) = \frac{1}{2}$  and  $\nabla f_2(1) = 2$
- Interpretation:
  - $f_1(x)$  is locally explosive at  $x^* = 0$  and locally stable at  $x^* = 1$
  - $f_2(x)$  is locally stable at  $x^* = 0$  and locally explosive at  $x^* = 1$

# Solow-Swan Growth Model



# Model of Growth and Capital

- An early growth model of economic growth is the [Solow-Swan model](#)
- Simple model. Details of the derivation for self-study/macro classes:
  - $k_t$  by capital per worker and  $y_t$  is total output per worker
  - $\alpha \in (0, 1)$  be a parameter which governs the marginal product of capital
  - $\delta \in (0, 1)$  is the depreciation rate (i.e., fraction of machines breaking each year)
  - $A > 0$  is a parameter which governs the total factor productivity (TFP)
  - $s \in (0, 1)$  is the fraction of output used for investment and savings

# Capital Dynamics

Then capital dynamics follow a nonlinear difference equation with steady state

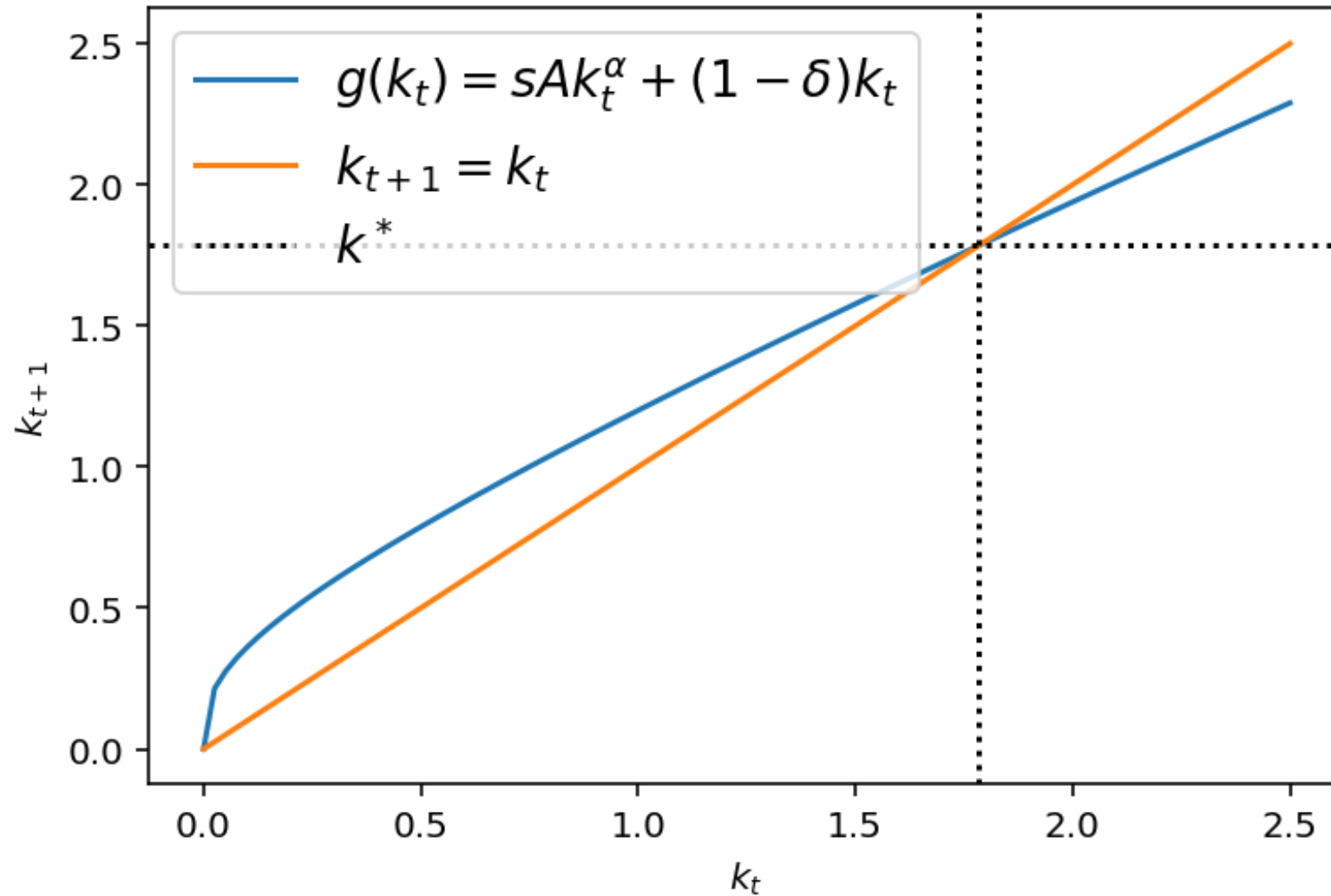
$$\begin{aligned}y_t &= Ak_t^\alpha \\k_{t+1} &= sy_t + (1 - \delta)k_t = sAk_t^\alpha + (1 - \delta)k_t \equiv g(k_t) \quad \text{given } k_0 \\k^* &\equiv \left( \frac{sA}{\delta} \right)^{\frac{1}{1-\alpha}}\end{aligned}$$

# Implementing the Solow-Swan Model

```
1 A, s, alpha, delta = 2, 0.3, 0.3, 0.4
2 def y(k):
3     return A*k**alpha
4 # "closure" binds y, A, s, alpha, delta
5 def g(k):
6     return s*y(k) + (1-delta)*k
7
8 k_star = (s*A/delta)**(1/(1-alpha))
9 k_0 = 0.25
10 print(f"k_1 = g(k_0) = {g(k_0):.3f},\
11 k_2 = g(g(k_0)) = {g(g(k_0)):.3f}")
12 print(f"k_star = {k_star:.3f}")
```

```
k_1 = g(k_0) = 0.546, k_2 = g(g(k_0)) = 0.828
k_star = 1.785
```

Plotting  $k_t$  vs.  $k_{t+1}$  verifies our  $k^*$



# Jacobian of $g$ at the steady state

$$\begin{aligned}\nabla g(k^*) &= \alpha s A k^{*\alpha-1} + 1 - \delta, \quad \text{substitute for } k^* \\ &= \alpha s A \frac{\delta}{s A} + 1 - \delta = \alpha \delta + 1 - \delta \\ &= 1 - (1 - \alpha)\delta < 1\end{aligned}$$

- Key requirements were  $\alpha \in (0, 1)$  and  $\delta \in (0, 1)$
- The spectral radius of a scalar is just that value itself.
- The spectral radius of  $\|\nabla g(k^*)\| < 1$ , a necessary condition for  $k^*$  stable
- **Aside:** macroeconomics, industrial organization, etc. this is related to contraction mappings and Blackwell's condition

# Simulation

```
1 # Generic function, takes in a function!
2 def simulate(f, X_0, T):
3     X = np.zeros((1, T+1))
4     X[:,0] = X_0
5     for t in range(T):
6         X[:,t+1] = f(X[:,t])
7     return X
8 T = 10
9 X_0 = np.array([0.25]) # initial condition
10 X = simulate(g, X_0, T) # use with our g
11 print(f"X_{T} = {X[:,T]}")
```

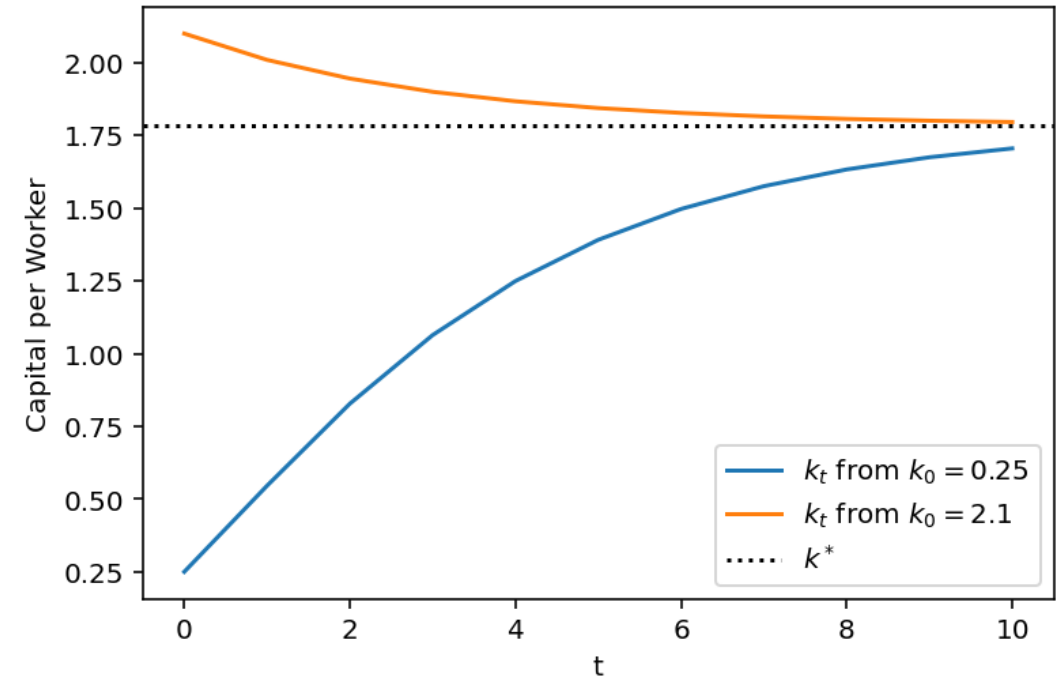
X<sub>10</sub> = [1.70531835]

# Capital Transition from $k_0 < k^*$ and $k_0 > k^*$

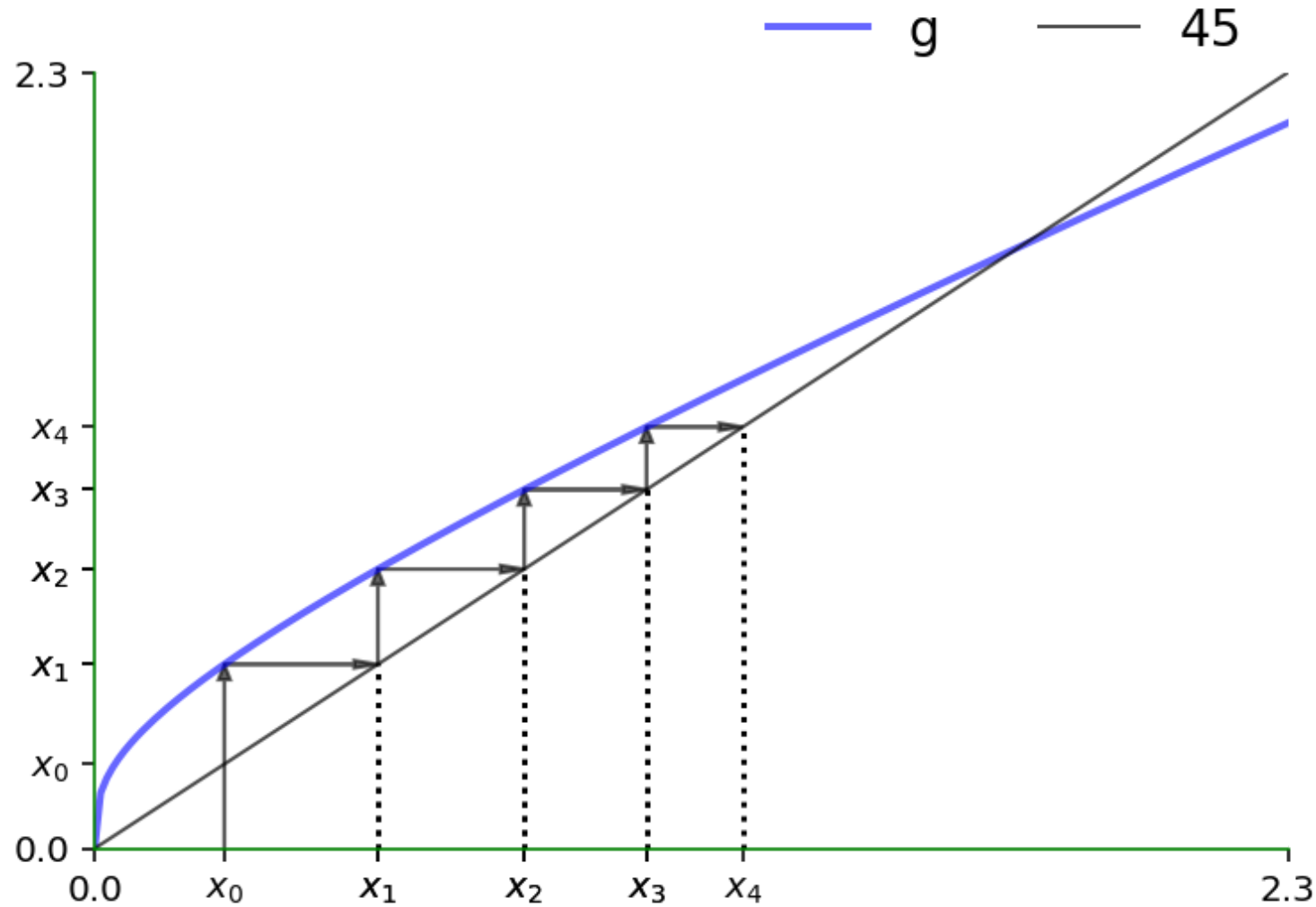
```

1 X_1 = simulate(g, X_0, T) # use with our g
2 X_2 = simulate(g, np.array([2.1]), T)
3 fig, ax = plt.subplots()
4 ax.plot(range(T+1), X_1.T,
5         label=r"$k_t$ from $k_0 = 0.25$")
6 ax.plot(range(T+1), X_2.T,
7         label=r"$k_t$ from $k_0 = 2.1$")
8 ax.set(xlabel="t", ylabel="Capital per Worker")
9 ax.axhline(y=k_star, linestyle=':',
10           color='black', label=r"$k^*$")
11 ax.legend()
12 plt.show()

```



# Trajectories Using the 45 degree Line

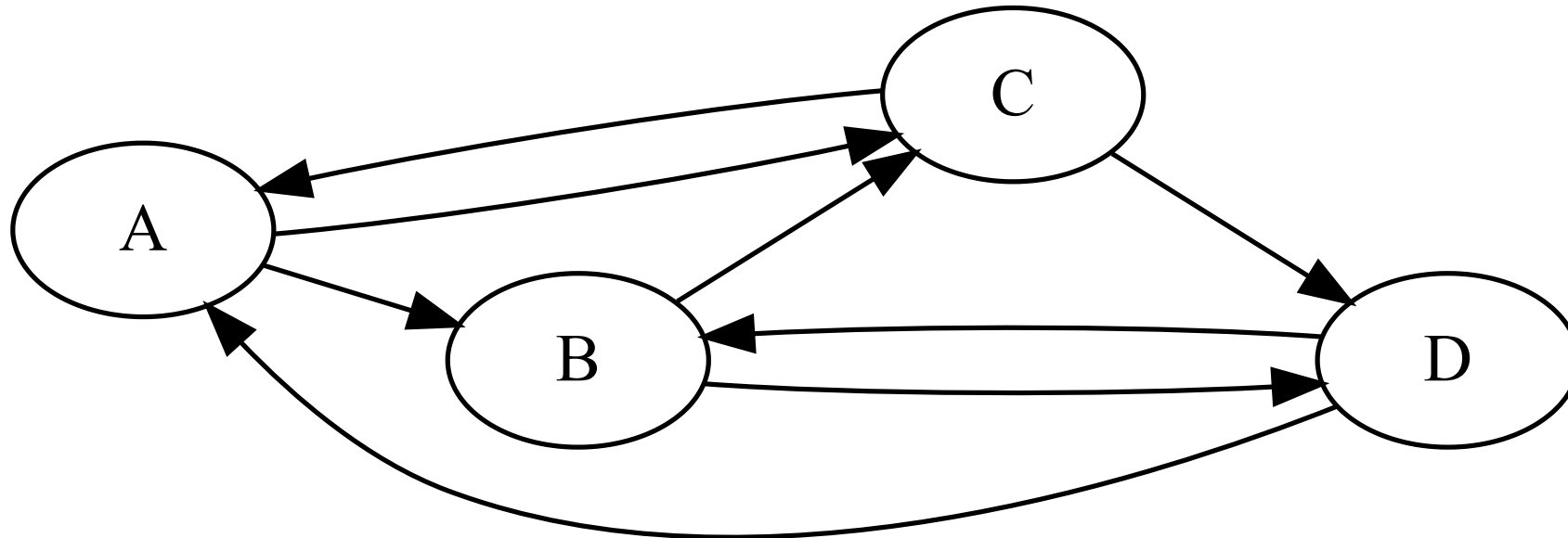




# PageRank and Other Applications

# Network of Web Pages

- Consider  $A, B, C, D$  as a set of web pages with links given below



# Create an Adjacency Matrix

- We can summarize the network of web pages with **1** or **0** if there is a link between two pages. Pages won't link to themselves
- This is in (arbitrary) order: A, B, C, D

$$M = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 \end{pmatrix}$$

# PageRank Algorithm

One interpretation of this is that you can

- Start on some page
- With equal probability click on all pages linked at that page
- Keep doing this process and then determine what fraction of time you spend on each page

# Probabilistic Interpretation

Alternatively,

- Start with a probability distribution,  $\mathbf{r}_t$  that you will be on any given page (i.e.  $r_{nt} \geq 0$  and  $\sum_{n=1}^4 r_{nt} = 1$ )
- Iterate the process to see the probability distribution after you click the next links
- Repeat until the probability distribution doesn't change.

# Adjacency Matrix to Probabilities

- To implement, we want to put the same probability on going to any link for a given page (i.e. each row)

$$S = \begin{pmatrix} 0 & 0.5 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0.5 \\ 0.5 & 0 & 0 & 0.5 \\ 0.5 & 0.5 & 0 & 0 \end{pmatrix}$$

# Probabilities Evolution

- Now, we can see what happens after we click on a page
- For a given  $r_t$  distribution of probabilities across page, I can see the new probabilities distribution as

$$r_{t+1} = Sr_t$$

- Motivation to learn more probability and Markov Chains (next set of lectures)

# Fixed Points and Eigenvectors

- What is a fixed point of this process?
- Eigenvector of  $S$  associated with  $\lambda = 1$  eigenvalue!
- The real PageRank is a little more subtle (adds in dampening) but the same basic idea
- Learn numerical algebra to use in practice. It is infeasible to actually compute the eigenvector of a huge matrix with a decomposition.