

# Markov Chains

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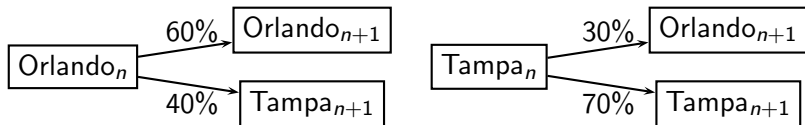
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**Example.** Suppose you run a rental company based in Orlando and Tampa, Florida. People often drive between the cities; cars can be picked up and dropped off in either city. Suppose that **historically**,



What distribution of cars can the company expect in the long run?

## Markov Chains

We will model this situation with a Markov Chain.

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We can represent the distribution of cars at time  $n$  with the vector

$$\vec{x}_n = \begin{bmatrix} o_n \\ t_n \end{bmatrix}.$$



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$$\vec{x}_n = \begin{bmatrix} o_n \\ t_n \end{bmatrix}. \text{ And so, } \vec{x}_{n+1} = \begin{bmatrix} o_{n+1} \\ t_{n+1} \end{bmatrix} = A \cdot \begin{bmatrix} o_n \\ t_n \end{bmatrix} = A\vec{x}_n.$$

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Given an initial distribution  $\vec{x}_0 = \begin{bmatrix} o_0 \\ t_0 \end{bmatrix}$ ,

the expected distribution of cars at time  $n$  is  $\vec{x}_n = \underline{\hspace{2cm}}$ .

## Markov Chains

For example, if the company starts off with twice as many cars in Orlando as in Tampa, then  $\vec{x}_0 = \begin{bmatrix} 2/3 \\ 1/3 \end{bmatrix}$ , so we expect

$$\vec{x}_1 = \begin{bmatrix} 0.6 & 0.3 \\ 0.4 & 0.7 \end{bmatrix} \begin{bmatrix} 2/3 \\ 1/3 \end{bmatrix} = \begin{bmatrix} \quad \\ \quad \end{bmatrix}.$$

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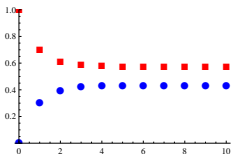
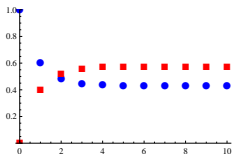
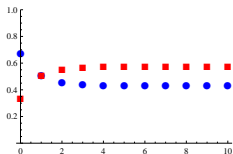
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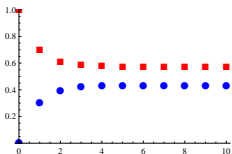
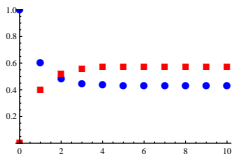
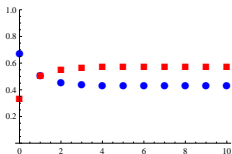


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How do we determine the expected distribution in the long run?

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In our example, the equilibrium distribution satisfies

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So solve:  $0.6o_{eq} + 0.3t_{eq} = o_{eq}$  and  $0.4o_{eq} + 0.7t_{eq} = t_{eq}$ .  
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★ There is no general rule for what the row sum will be.