CS70: Jean Walrand: Lecture 37.

Statistics are Confusing; What's next

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Statistics are Confusing; What's next

- Simpson's Paradox
- Bertrand's Paradox
- Confirmation Bias
- Thinking, fast and slow
- The Problem with Statistics
- What's next?

Simpson's Paradox

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College	F. Appl.	F. Adm.	% F. Adm.	M. Appl.	M. Adm.	% M. Adm.
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B	20	20	100%	800	720	90%
Total	1000	510	51%	1000	800	80%

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Female students happen to apply to a college that admits fewer students.

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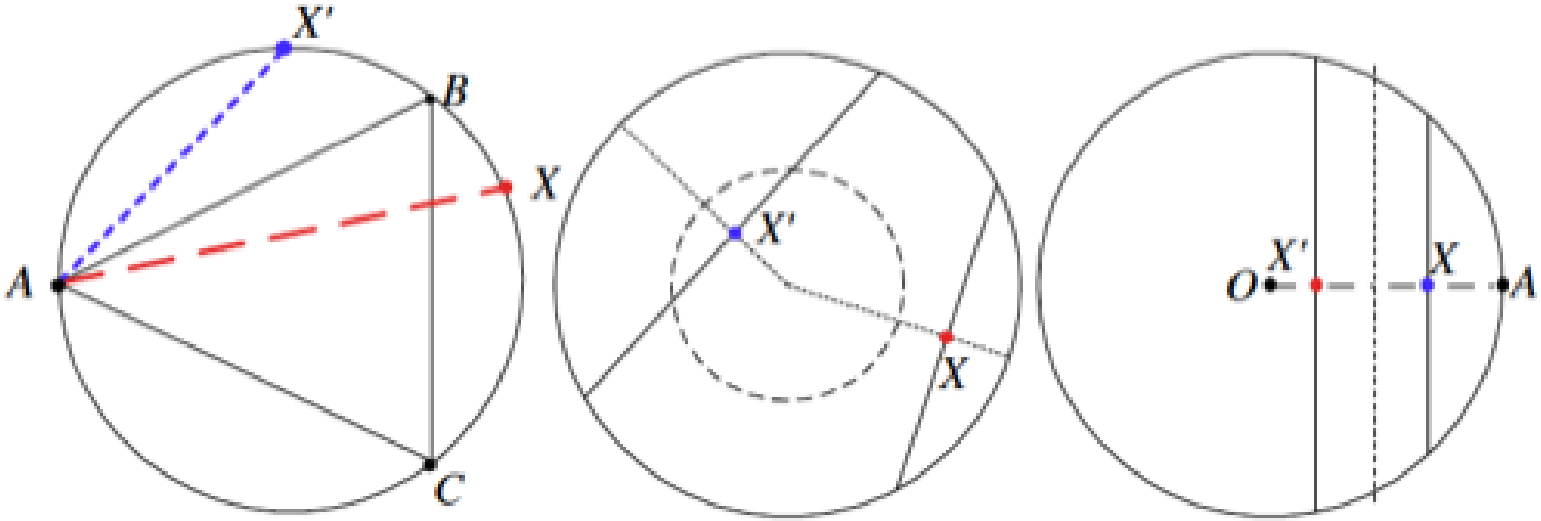

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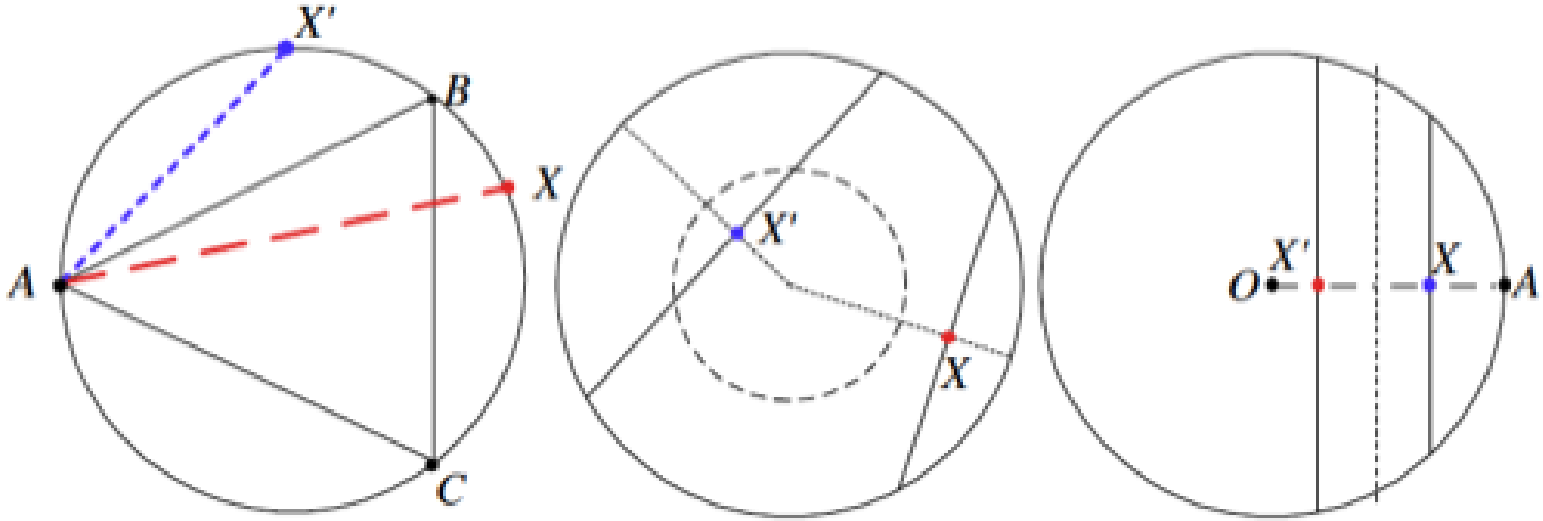

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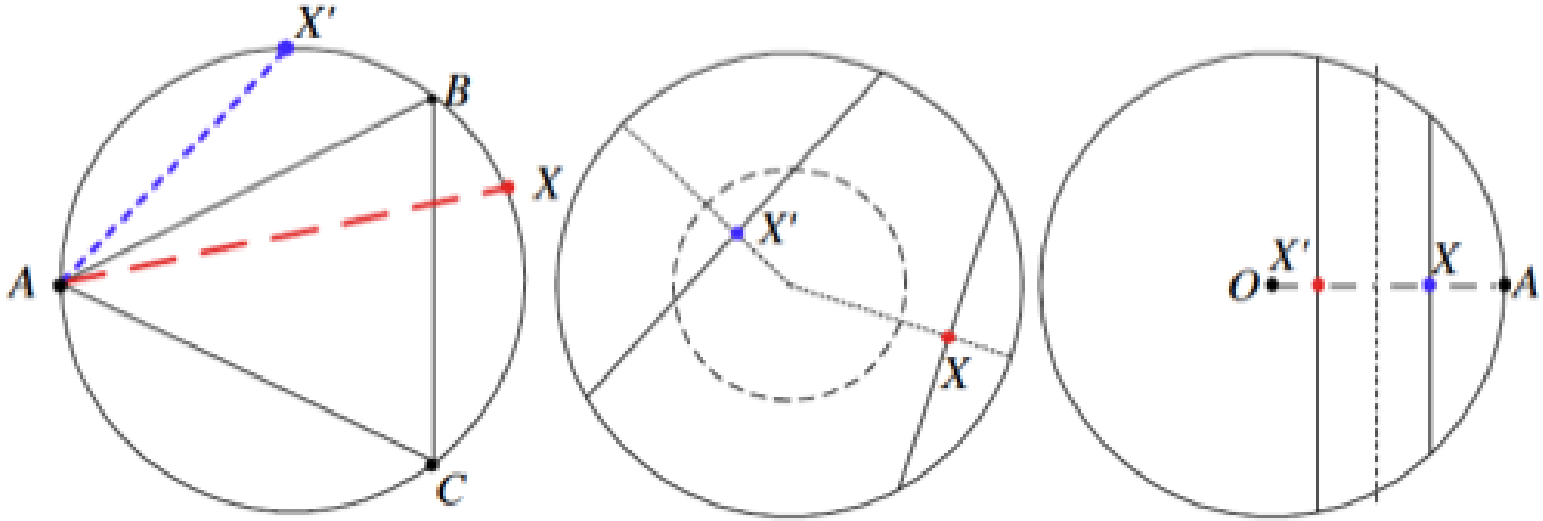

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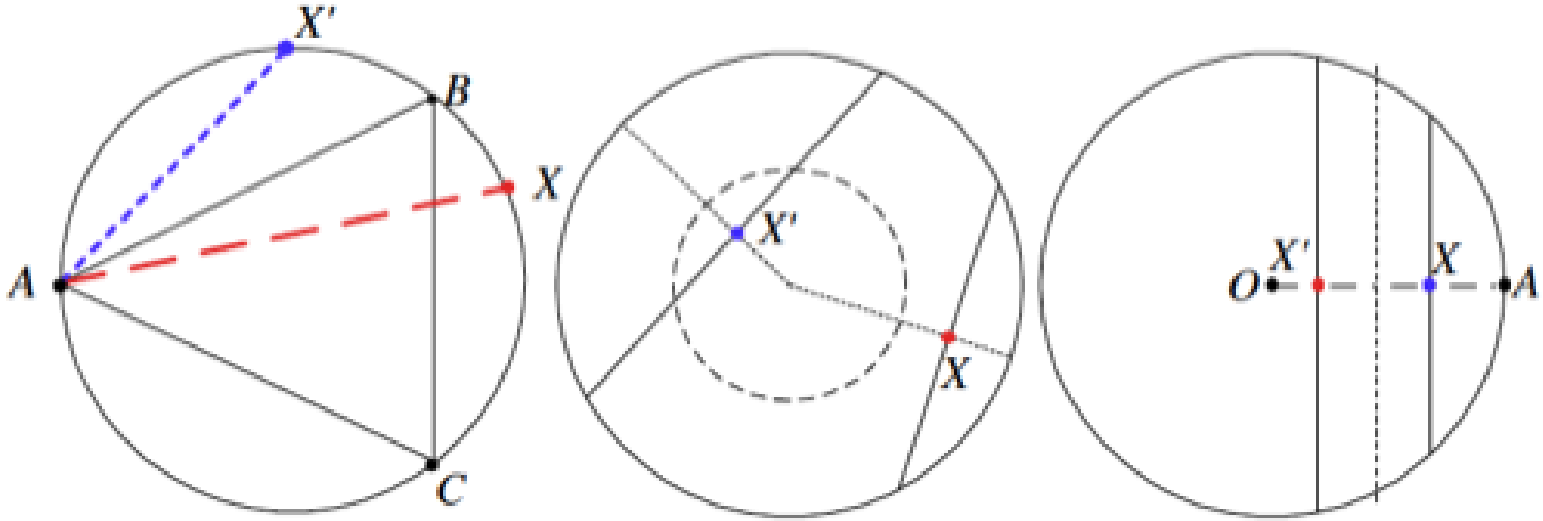

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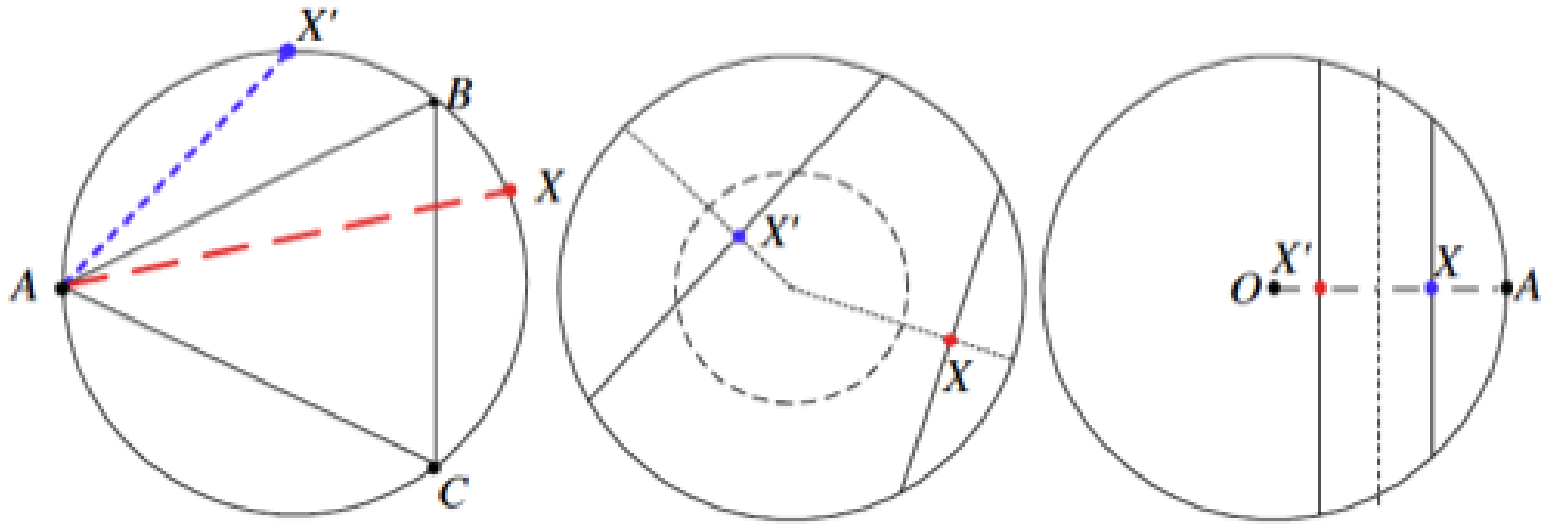

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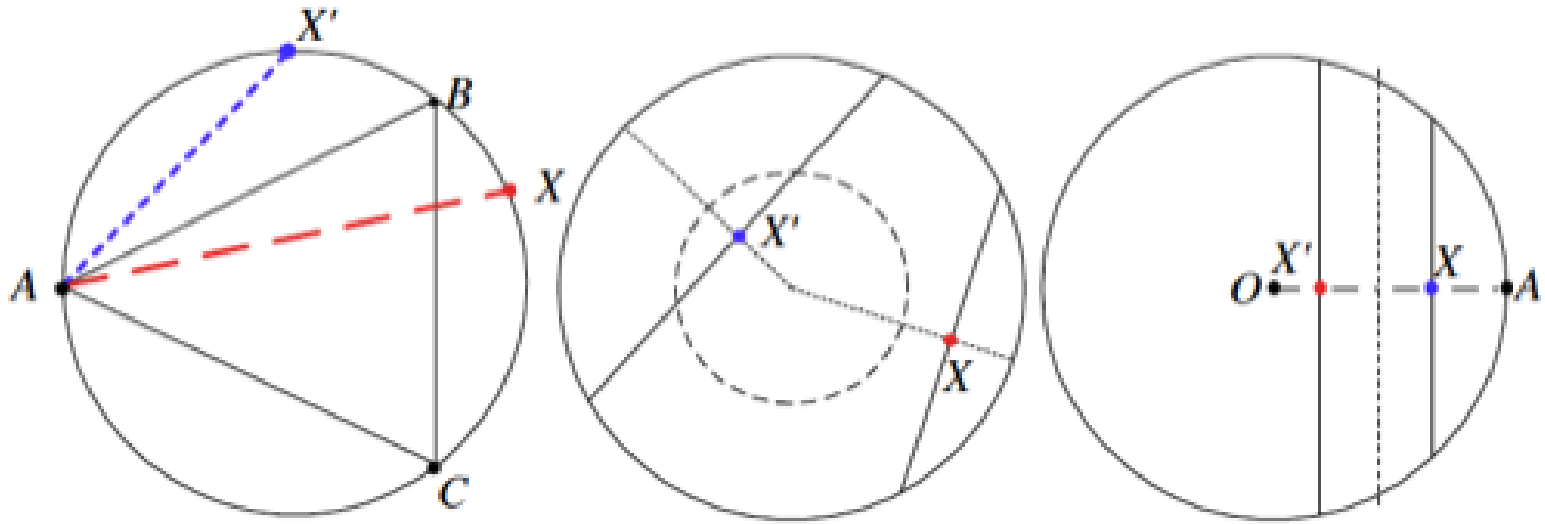

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- $1/2$ if you choose a point X uniformly at random on a radius and draw the chord perpendicular to the radius that goes through X (right).

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Confirmation Bias: An experiment

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Surprisingly, people tend to be reinforced in their original belief, even when the evidence accumulates against it.

Thinking, fast and slow

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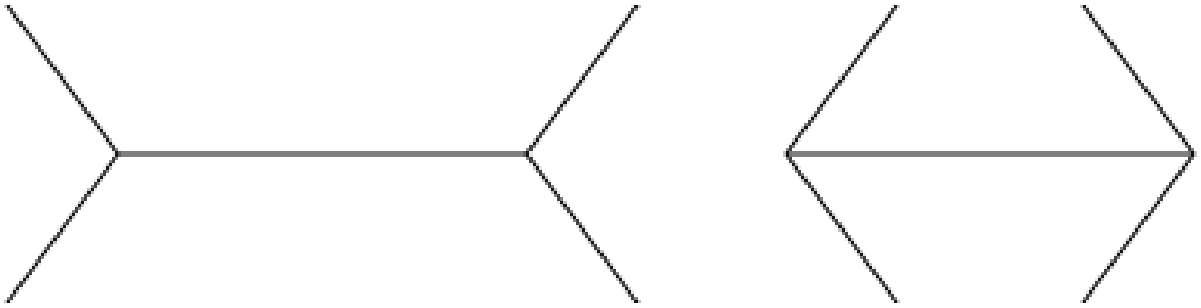

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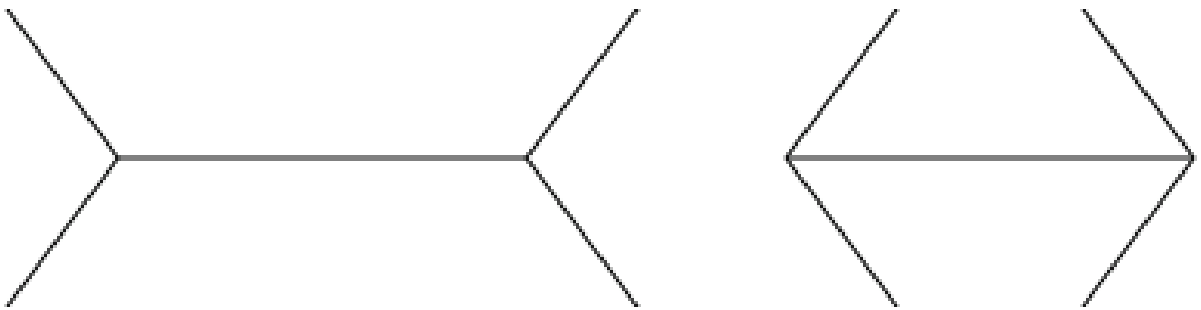

It is difficult to think clearly!

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- Beware of statistics reported in the media!

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- EE229A: Information Theory; EE229B: Coding Theory.

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What's Next?

Professors, I loved this course so much! I want to learn more about discrete math and probability!

Funny you should ask! How about

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- EE126: Probability in EECS: An Application-Driven Course: PageRank, Digital Links, Tracking, Speech Recognition, Planning, etc. Hands on labs with python experiments (GPS, Shazam, ...).
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Finally,

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Thanks to the CS70 Staff!!