CS70: Jean Walrand: Lecture 38.

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Female students happen to apply more to the college that admits fewer students.

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- Beware of statistics reported in the media!

Choosing at Random: Bertrand's Paradox

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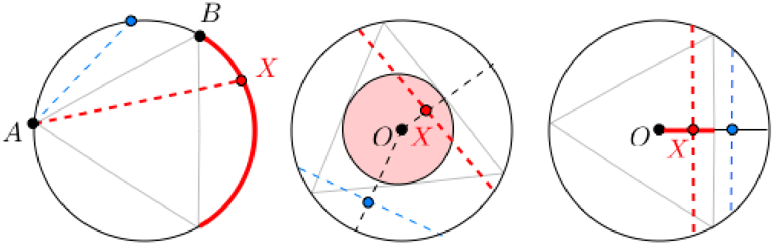

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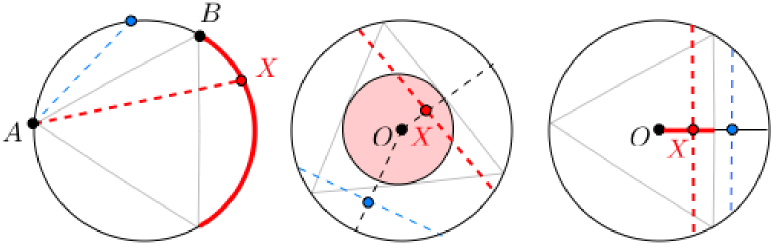

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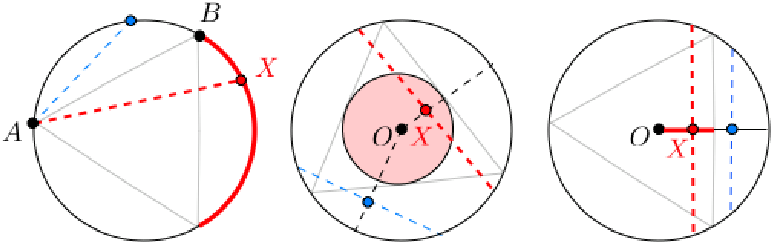

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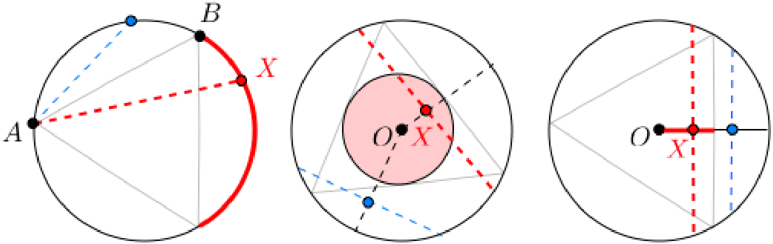

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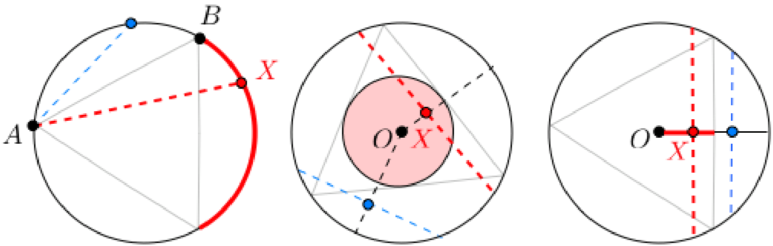

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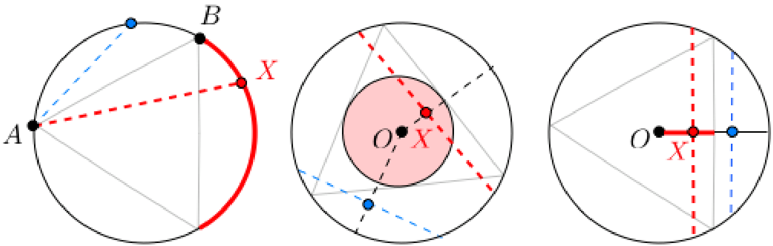

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- $1/2$ if you choose a point X uniformly at random on a given radius and draw the chord perpendicular to the radius that goes through X (right).

Confirmation Bias

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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.

Being Rational: ‘Thinking, Fast and Slow’

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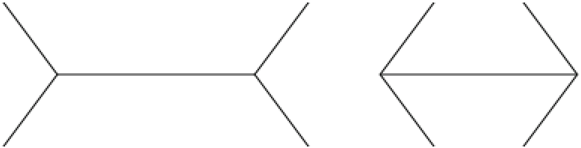

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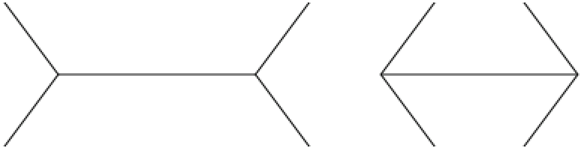

It is difficult to think clearly!

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What's Next?

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

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Final Thoughts

Final Thoughts

More precisely:

Final Thoughts

More precisely: Some thoughts about the final ....

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides;

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides; Notes;

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides; Notes; Discussion Problems;

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides; Notes; Discussion Problems; HW

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides; Notes; Discussion Problems; HW
- TA Office Hours,

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides; Notes; Discussion Problems; HW
- TA Office Hours, Prof. Office Hours,

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides; Notes; Discussion Problems; HW
- TA Office Hours, Prof. Office Hours, Reviews by TAs

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides; Notes; Discussion Problems; HW
- TA Office Hours, Prof. Office Hours, Reviews by TAs
- Next week: reviews during normal lecture hours:

Final Thoughts

More precisely: Some thoughts about the final ....

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- Next week: reviews during normal lecture hours:
  - Discrete Math (Monday);

Final Thoughts

More precisely: Some thoughts about the final ....

How to study for the final?

- Lecture Slides; Notes; Discussion Problems; HW
- TA Office Hours, Prof. Office Hours, Reviews by TAs
- Next week: reviews during normal lecture hours:
  - Discrete Math (Monday);
  - Probability (Wednesday).

Parting Thoughts

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You have learned a lot in this course!

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Proofs,

Parting Thoughts

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Proofs, Graphs,

Parting Thoughts

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Proofs, Graphs, Mod(p),

Parting Thoughts

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Proofs, Graphs, Mod(p), RSA,

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Proofs, Graphs, Mod(p), RSA, Reed-Solomon, Decidability, Probability, ... , how to handle stress,

Parting Thoughts

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Proofs, Graphs, Mod(p), RSA, Reed-Solomon, Decidability, Probability, ... , how to handle stress, how to sleep less,

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Thanks to the CS70 Staff:

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See you on Wednesday.