

From Rules to Machine Learning to Deep Learning

Laura E. Boucheron

College of Engineering

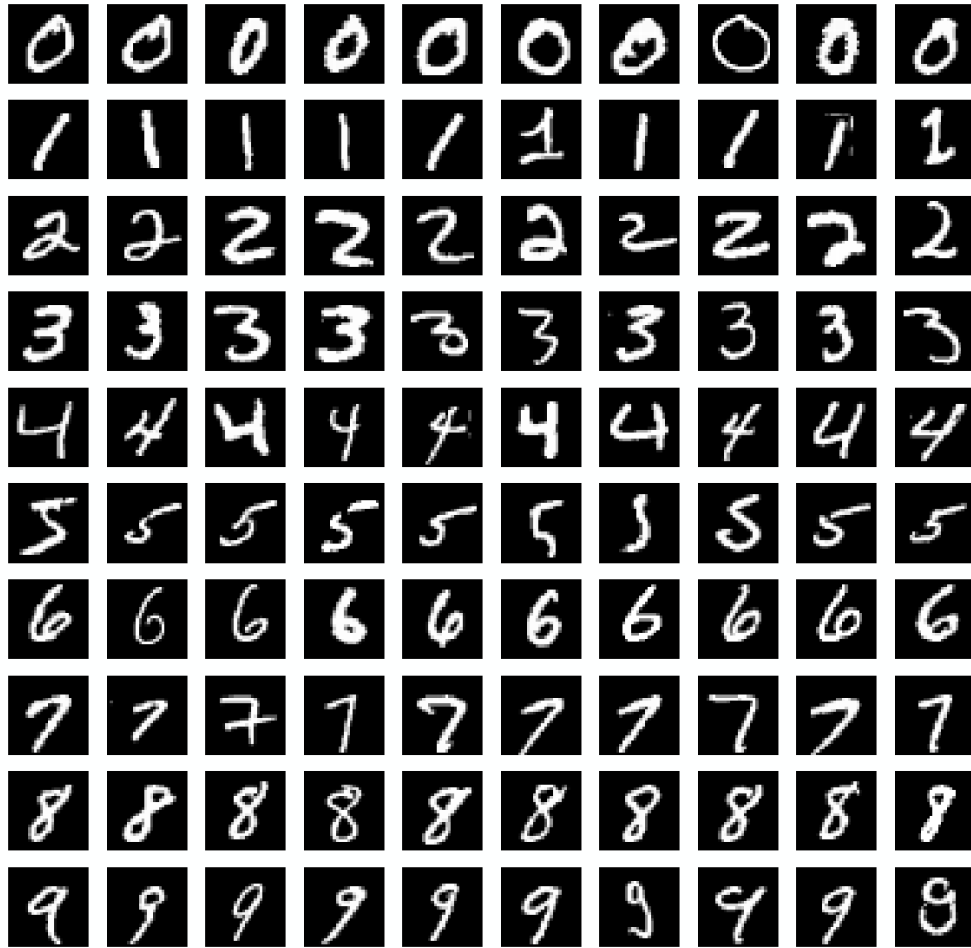
Klipsch School of Electrical &
Computer Engineering

The logo for New Mexico State University, featuring the letters 'NM' in a large, bold, serif font above the words 'STATE' and 'UNIVERSITY' in a smaller, bold, sans-serif font. The text is white and set against a dark red square background.

NM
STATE
UNIVERSITY

BE BOLD. Shape the Future.

The MNIST Dataset



- 70,000 28x28 pixel digitized images of handwritten digits 0 through 9
- Considered a standard benchmark dataset
- Small enough to
 - Fit in memory
 - Run on a modest machine
- Large enough to
 - Span a reasonable range of appearances
 - Solve an interesting problem

Rules:
**How might we as
humans describe the
difference between
handwritten digits?**



BE BOLD. Shape the Future.

Discriminating b/w 1 and 7

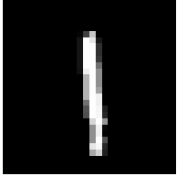
1

7

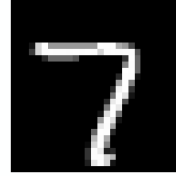


Discriminating b/w 1 and 7

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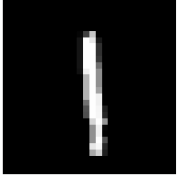


7



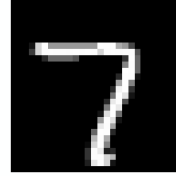
Discriminating b/w 1 and 7

1



- One line segment

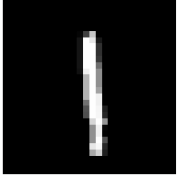
7



- Two line segments

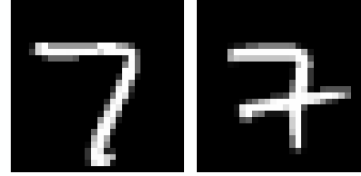
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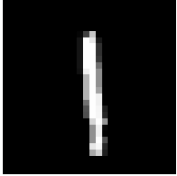
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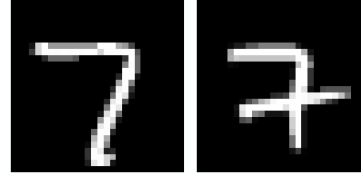
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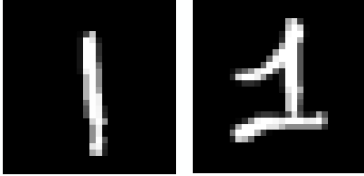


- Two line segments

- OR three line segments

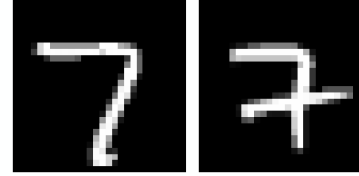
Discriminating b/w 1 and 7

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- One line segment

7



- Two line segments
- OR three line segments

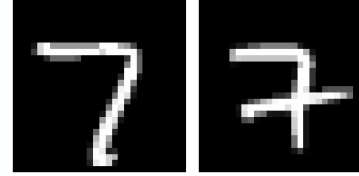
Discriminating b/w 1 and 7

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- One line segment
- OR three line segments where two are not perpendicular to the third

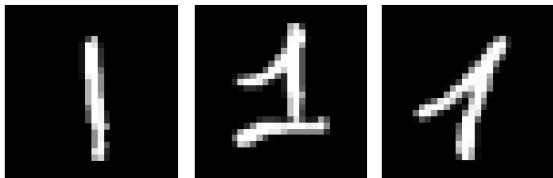
7



- Two line segments
- OR three line segments ...where two are perpendicular to the third

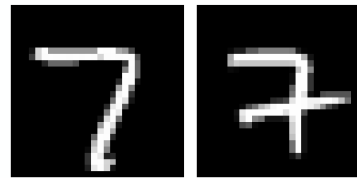
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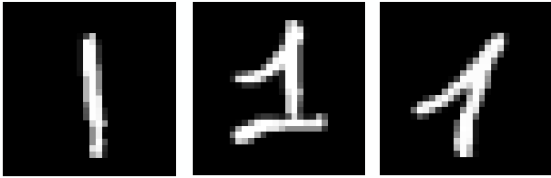
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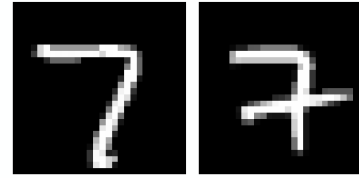
Discriminating b/w 1 and 7

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- One line segment
- OR three line segments where two are not perpendicular to the third
- OR two line segments with a small angle between them

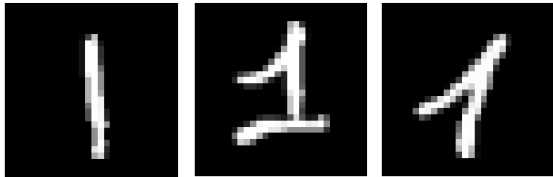
7



- Two line segments ...with a large angle between them
- OR three line segments ...where two are perpendicular to the third

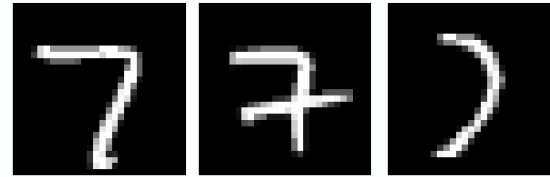
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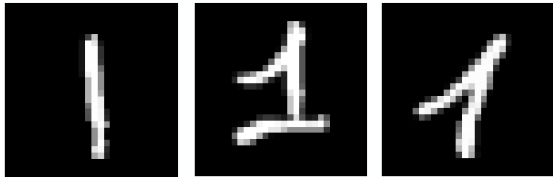
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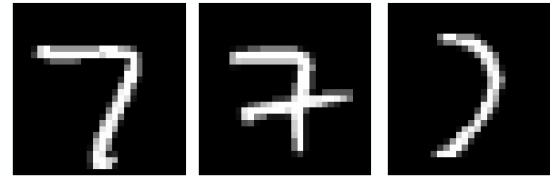
Discriminating b/w 1 and 7

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- One line segment
...which has a small curvature to it
- OR three line segments where two are not perpendicular to the third
- OR two line segments with a small angle between them

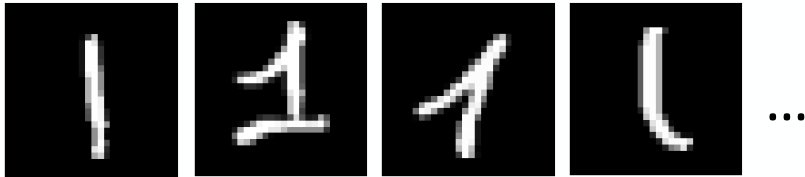
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- Two line segments
...with a large angle between them
- OR three line segments
...where two are perpendicular to the third
- OR one line segment which has a large curvature to it

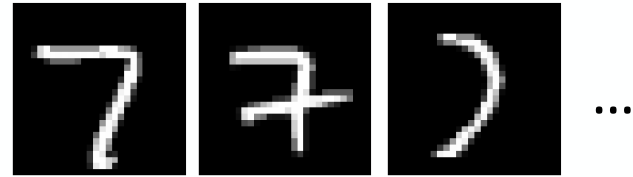
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- ...

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- OR three line segments
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Rule-Based Learning

- Leverage the **human** to provide **labeled training data** (example images matched to labels)—Defines the **ground truth**



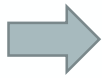
Example Images

“3”

Ground truth

Rule-Based Learning

- Leverage the **human** to provide **labeled training data** (example images matched to labels)—Defines the **ground truth**
- Leverage the **human** to work with specific examples to define a set of discriminatory features—Defines the **feature space**



Example Images

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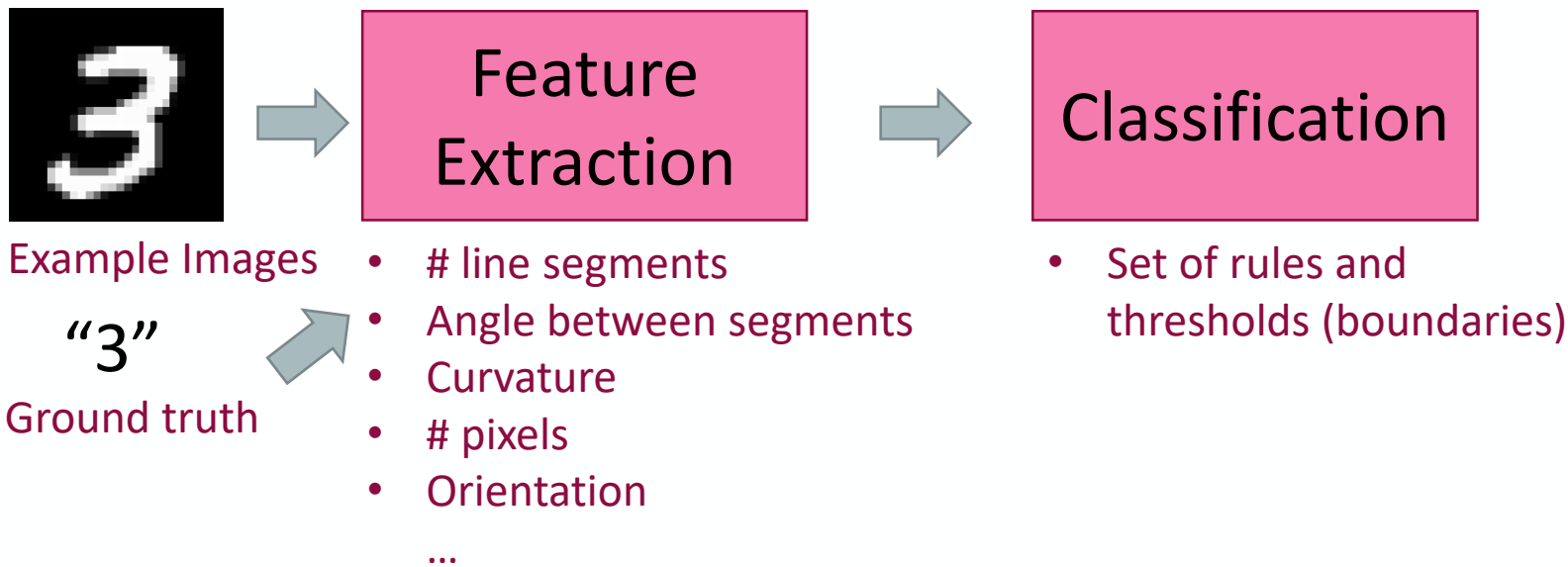
Ground truth



- # line segments
- Angle between segments
- Curvature
- # pixels
- Orientation
- ...

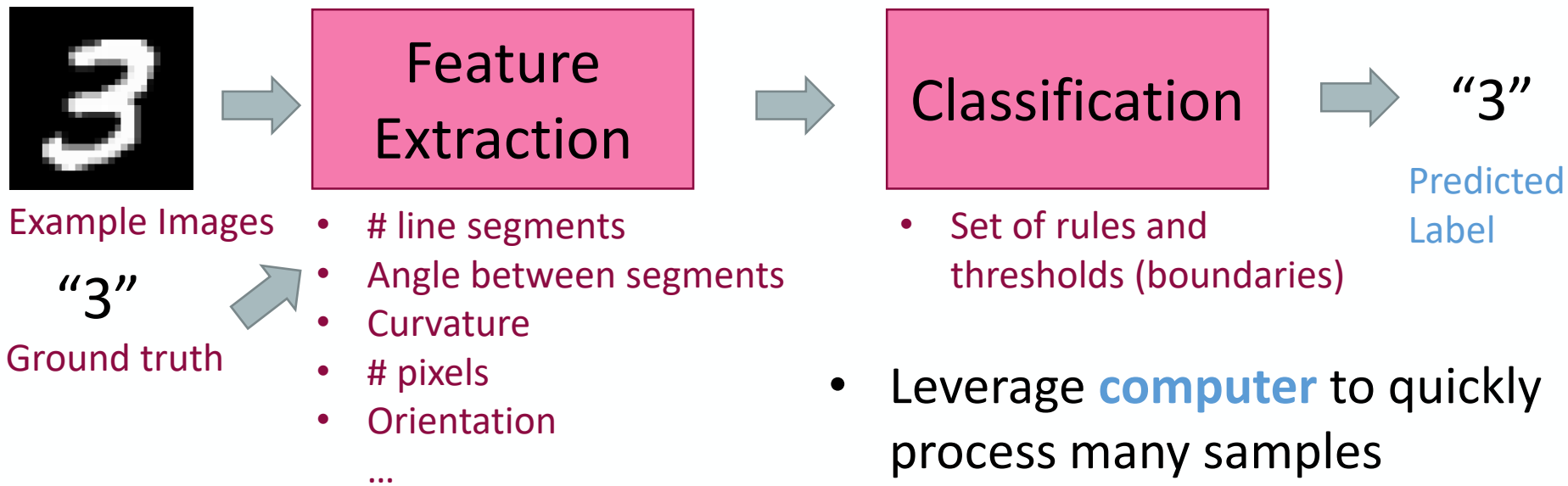
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- Leverage the **human** to use those features to discriminate between digits—Defines the **decision boundary**



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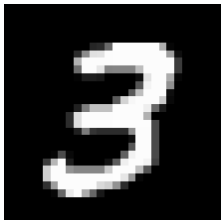


**Machine Learning:
How can we leverage
computers to sift
through the features
and learn to
discriminate between
handwritten digits?**



Classical Machine Learning: Feature Extraction->Classification

- Leverage the **human** to provide **labeled training data** (example images matched to labels)—Defines the **ground truth**



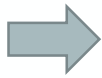
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Classical Machine Learning: Feature Extraction->Classification

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Feature
Extraction

Example Images

- # line segments
- Angle between segments
- Curvature
- # pixels
- Orientation

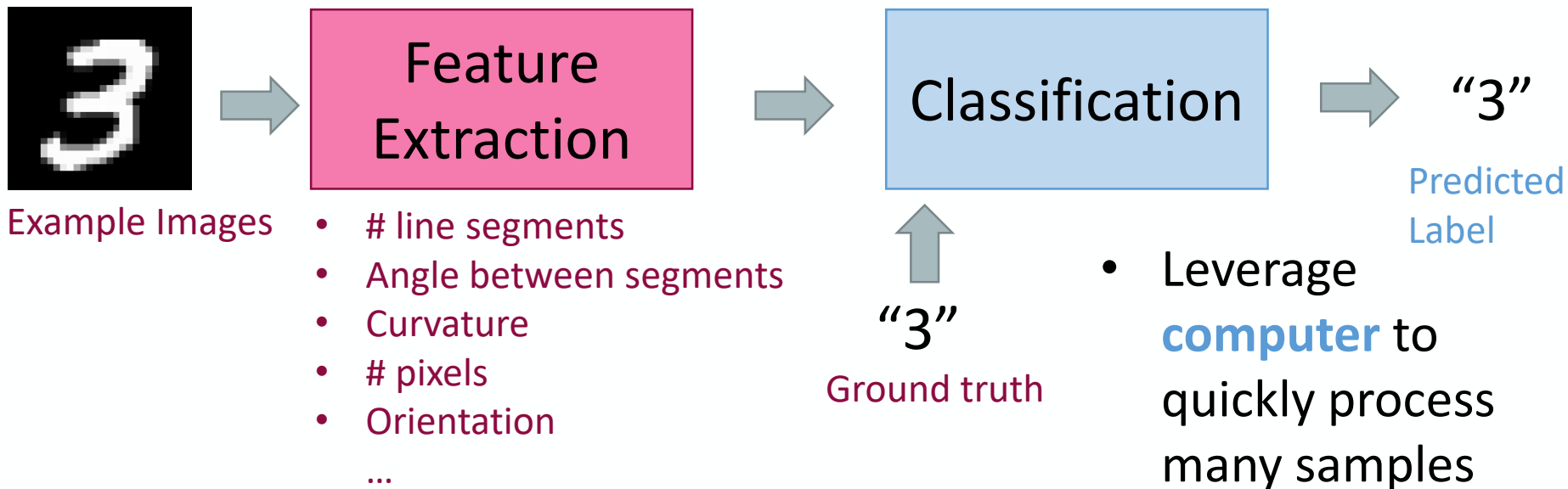
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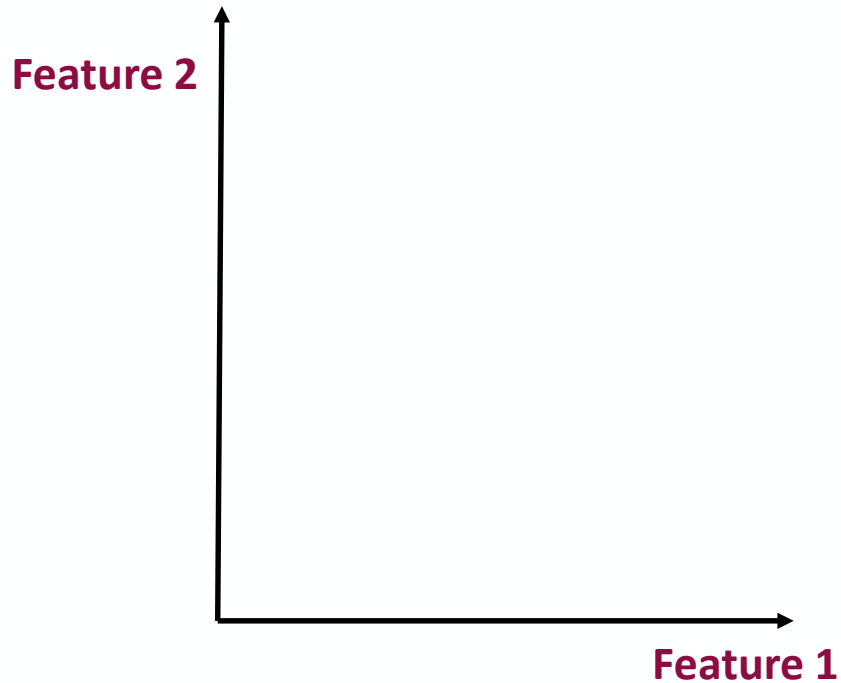
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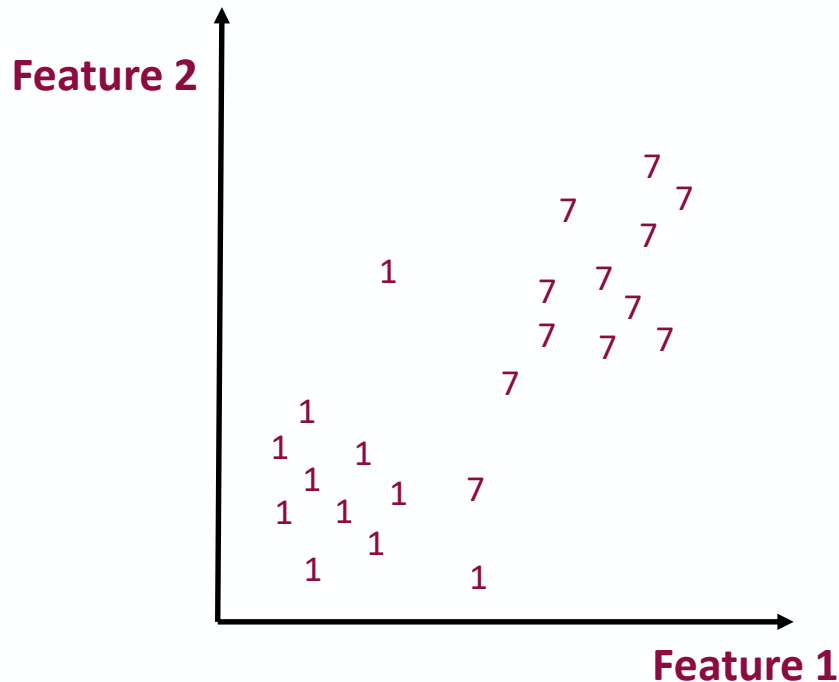
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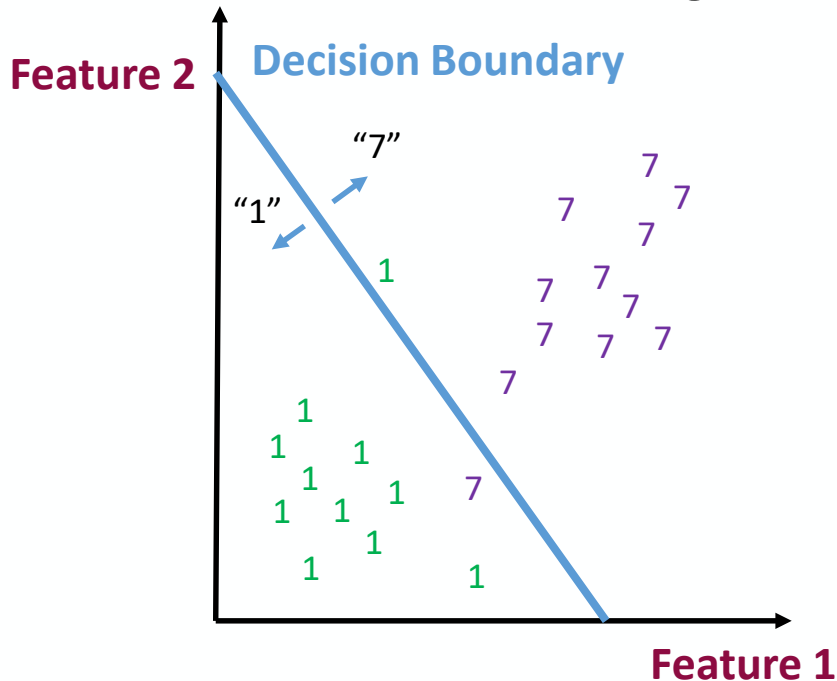
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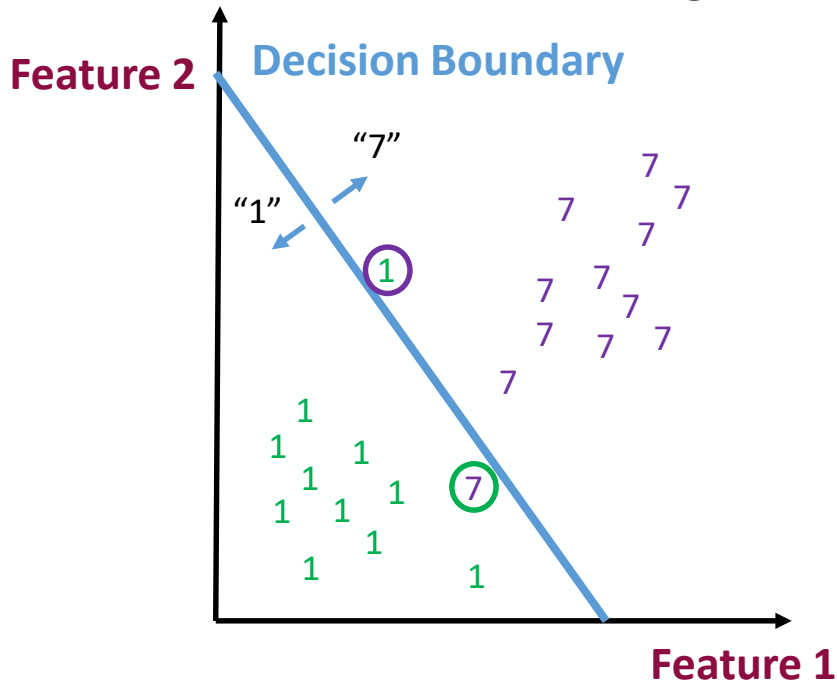
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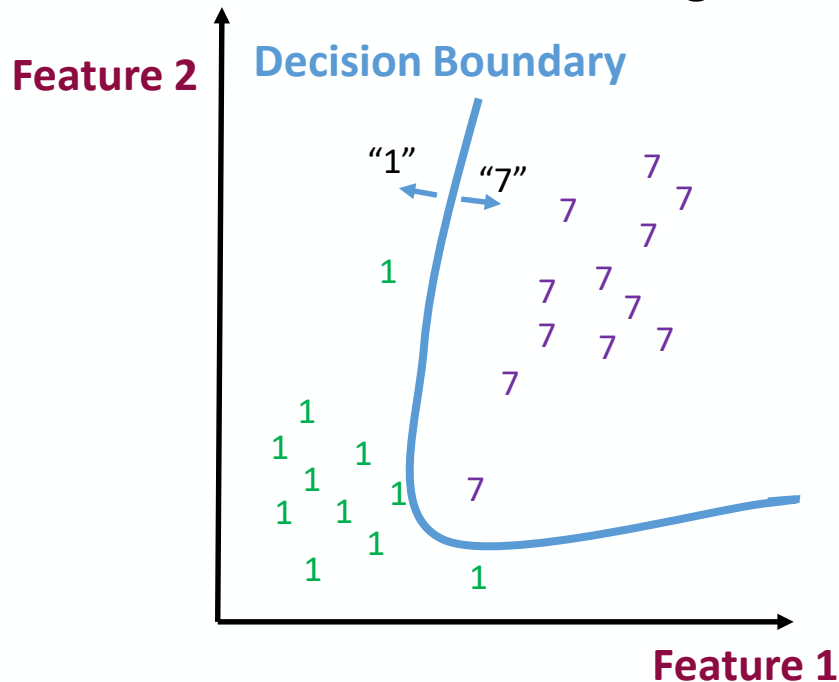
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- Misclassifications: ○ ○
 - Are they due to a **feature space** which is not descriptive enough?
 - Are they due to a **decision boundary** that is not appropriate for the space?
 - Are they due to not enough **training data**?
 - Are they just difficult samples to classify?

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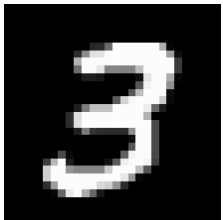
**Deep Learning:
How can we leverage
computers to learn
the features AND
how to use those
features to
discriminate between
handwritten digits?**



BE BOLD. Shape the Future.

Deep Learning: Feature Extraction & Classification

- Leverage the **human** to provide **labeled training data** (example images matched to labels)—Defines the **ground truth**



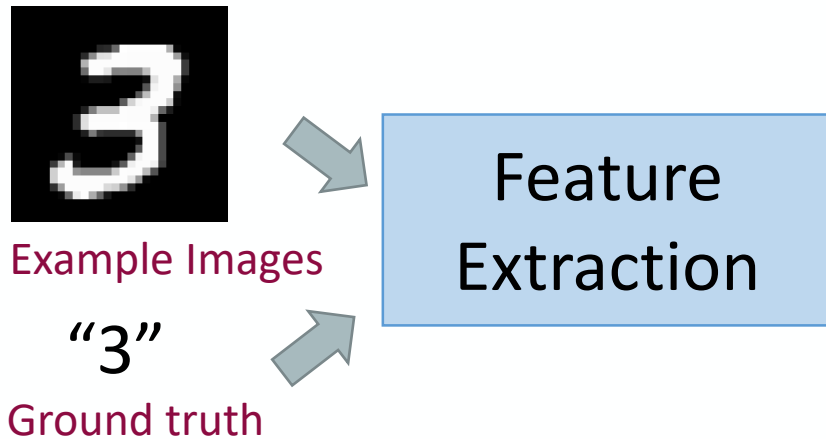
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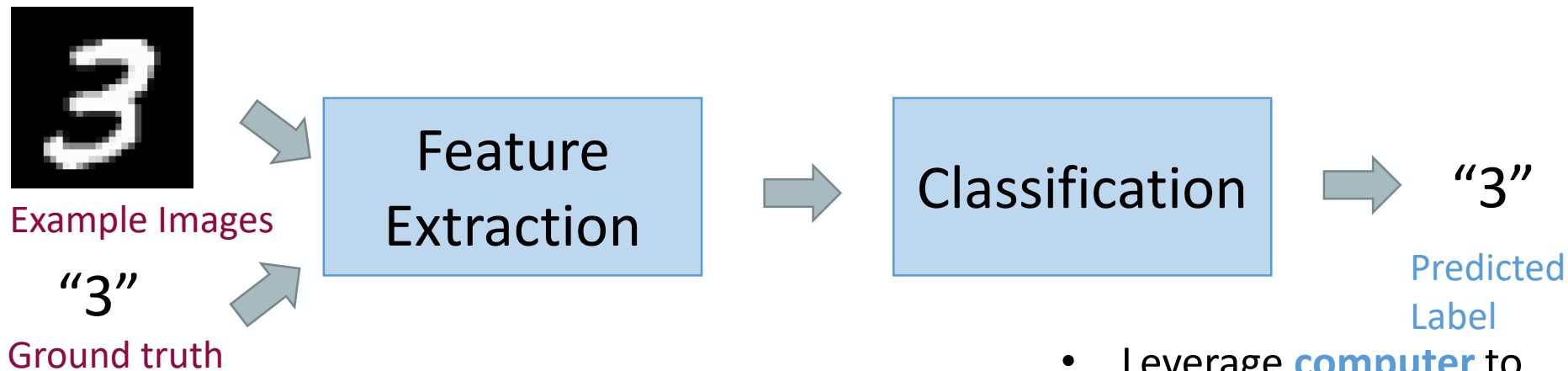
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- Leverage **computer** to quickly process many samples

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