Perturbation Theory for the Information Bottleneck

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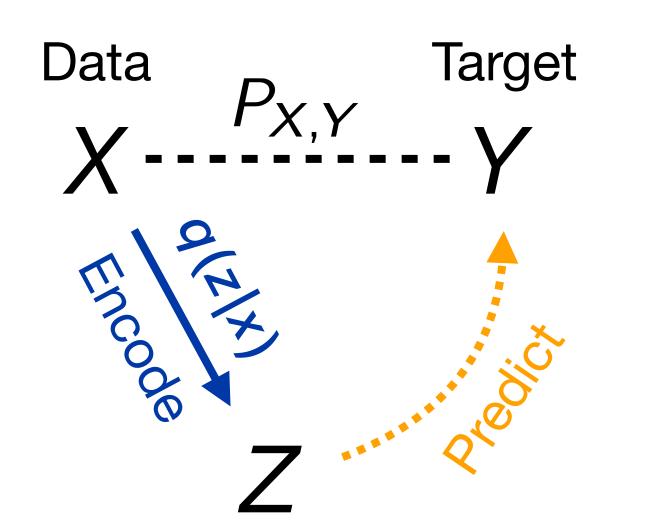
Extracting 'relevant' information from data underpins all forms of learning



Classifying handwritten digits requires extracting the *right* features from the space of pixels

The *right* features depend on what we want to know, eg, the digit, identity of writer, or brand of pen/pencil

Relevant information is the bits that can predict the 'target'



Encoder q(z|x) defines a mapping from X to Z that compresses X by discarding irrelevant information

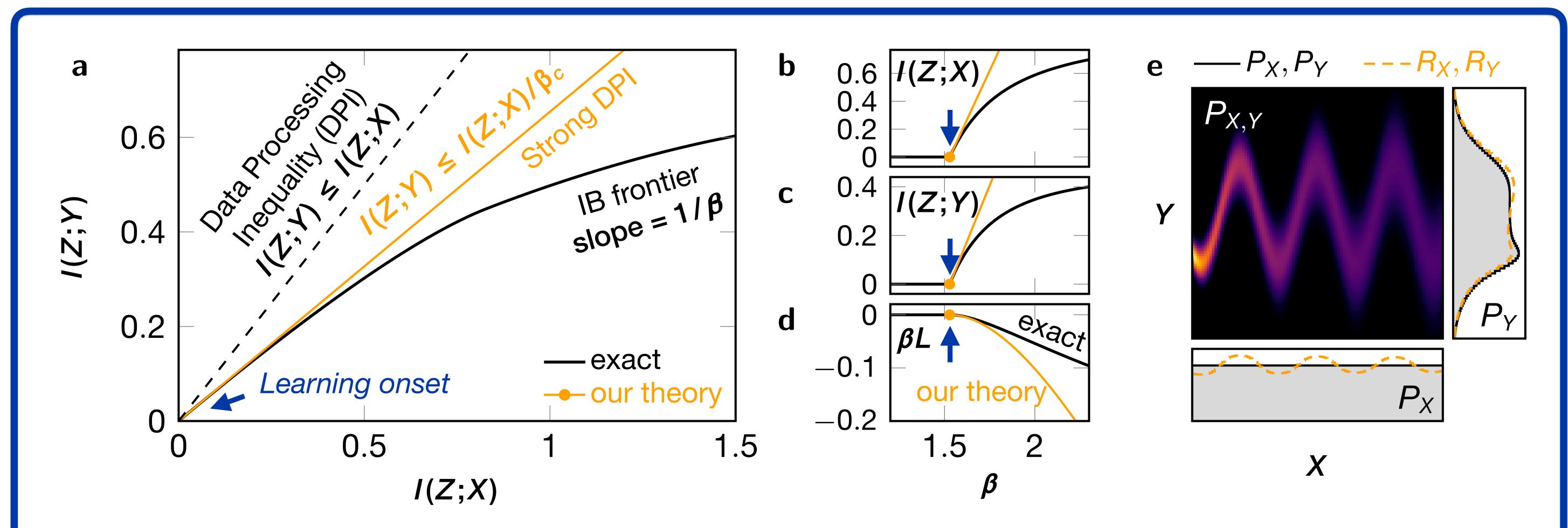
Representation of relevant information in *X*

In information bottleneck (IB), relevant information extracting is optimization

min
$$L$$
 with $L = I(Z;X) - \beta I(Z;Y)$
 $q(z|x)$ favors
compression prediction

 β controls compression-prediction trade-off

While precise and appealing, the IB problem is analytically intractable in general



Our theory predicts the maximum 'relevant' information ratio $(1/\beta_c)$ and connects the learning onset in the information bottleneck problem to the strong data processing inequality

Relevant information per extracted bit must be bounded from above

Relevant information ratio $\frac{I(Z;Y)}{I(Z;X)} \leq \beta_c^{-1} \leq 1$ strong data processing inequality

- $1/\beta_c$ = maximum relevant information ratio
- No informative representation for $\beta \leq \beta_c$
- $\beta = \beta_c$ marks the IB learning onset

Our analytical results for learning onset have potential implications in fundamental research and in practice

Maximum relevant information ratio $(1/\beta_c)$

- Related to contraction coefficient in information theory [Anantharam etal arXiv:1304.6133]
- Tight bound of the thermodynamic efficiency in predictive systems [Still etal PRL 2012]
- Useful measure of correlations [Kim etal NeurIPS 2017]
- Might help tune hyperparameters in deep learning techniques such as VIB [Wu etal Entropy 2019]