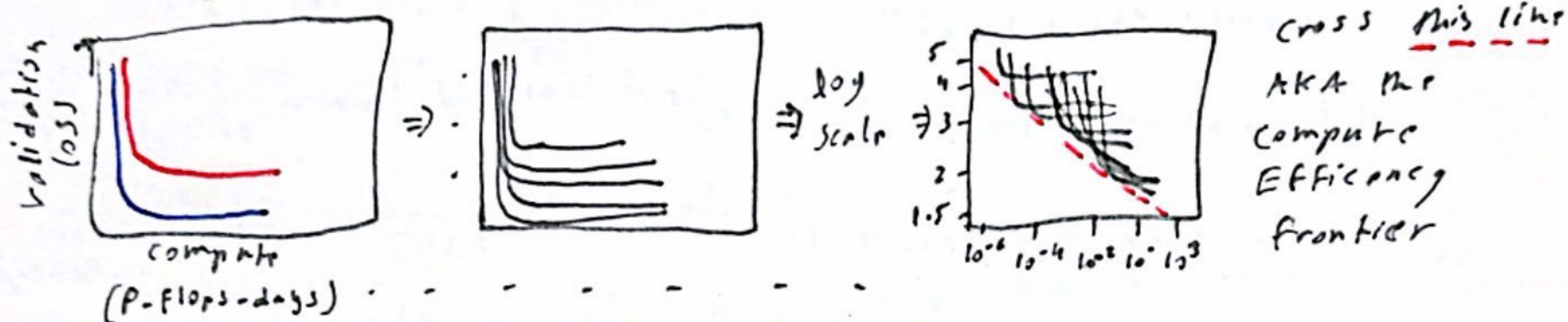
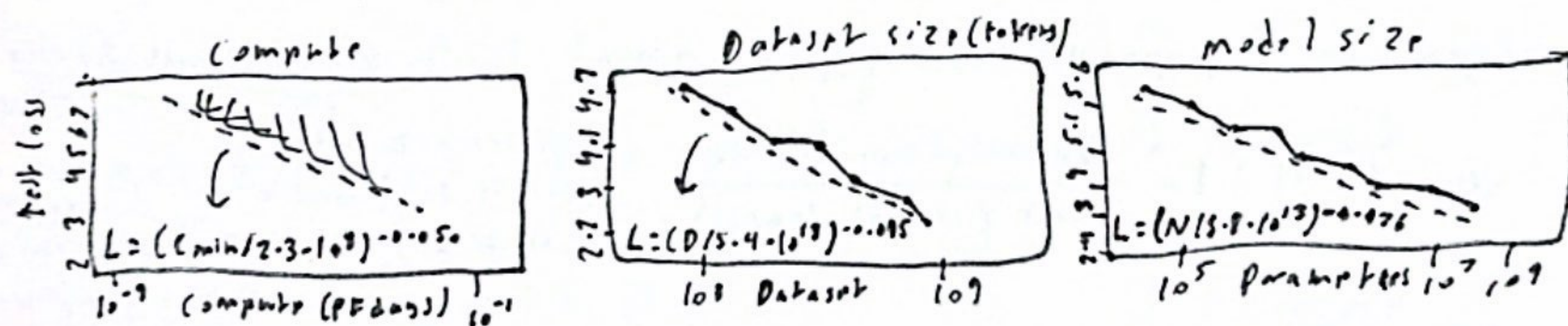


Neural scaling Laws

- as we train a AI model its error rate generally drops off quickly and then levels off if we train a larger model it will achieve a lower error rate but requires more compute
- Scaling to larger and larger models we end up with a family of curves switching to log scale a trend emerges, where no model can cross this line AKA the Compute Efficiency Frontier



- This trend is one of three neural scaling laws that have been observed
- error rate scales in a similar way with compute, Model size and Data set size, and does not depend much on model architecture or other Algorithmic details.



- on log plots these show straight lines and the slope of each line is equal to the exponent of fit equation (L) Larger exponents make for steeper lines and more rapid performance improvement.

Feature importance.

mostly used in decision trees

- take for ex decision trees they often overfit when unconstrained, meaning when we allow the tree to grow without any restrictions (like max depth, min samples per leaf etc) it can create a model that's too complex and overfits the training data, this leads to poor generalization to new unseen data basically memorizing the train set without learning the patterns. to solve this we can use Feature importance is a way to measure relative importance of each feature in a decision tree higher the Feature importance the more important the feature for predictions we can use Feature importance to identify important features and it works by looking at how much each feature contributes to reducing uncertainty in the data at each split in the tree.