Neural Network design

In addition to learning *how* to use Neural Networks, we hope this course has stimulated your curiosity.

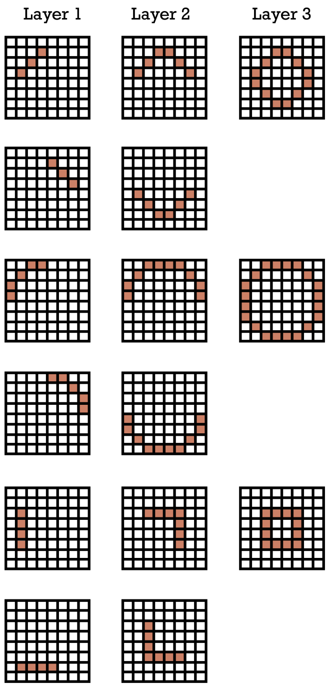
What strikes me as particularly curious:

- Neural Networks create representations allowing the Head Layer to solve a Classical ML task
- We don't know *how* these representations are created
- We certainly have not given any explicit instruction or requirement
- Yet the representation seems to be both useful for a particular task
- And *Transferable* to other tasks

We saw how a Neural Network for a vision task

- Seems to learn complex concepts
    - "Dimensions of meaning"
    - From smaller parts

Features by layer



So too we saw that Word Embeddings and the "Predict the next word" task seem to learn dimensions of meaning.

Both Images and Text feel like complex domains

- Yet a mechanical process (training on examples) seem to "discover" meaning
- Without explicit direction or explanation of the domains

Another curiosity: complex tasks (e.g. NLP, image recognition) are solved with *simple* programs.

The "art" of Neural Networks is *not* highly skilled programming but instead

- Being clever and diligent in acquiring enough training examples
- Creating a Loss Function that captures the essence of the problem

For example: Neural Style Transfer is a task that

- Takes one image (the "Content Image")
- And an artistic style, as expressed by a "Style Image"
- Produces a new image that re-expresses the Content Image in the style of the Style Image

Content Image	Style Image

Generated Image

The "trick" in solving this task is in writing the Loss function

- Not in designing the network
- Once the Loss function has been created
- We then apply the skills we learned to minimize Loss Functions
- And the task is solved

Without going into detail the Loss Function has two parts

- A "content loss": the generated image $\vec{\mathbf{x}}$ should be close to the Source Image $\vec{\mathbf{p}}$
- A "style loss": the style of the generated image $\vec{\mathbf{x}}$ and the Style Image $\vec{\mathbf{a}}$ should be close

$$\mathcal{L} = \mathcal{L}_{\text{content}}(\vec{\mathbf{p}}, \vec{\mathbf{x}}) + \mathcal{L}_{\text{style}}(\vec{\mathbf{a}}, \vec{\mathbf{x}})$$

To be sure: there is some cleverness involved in

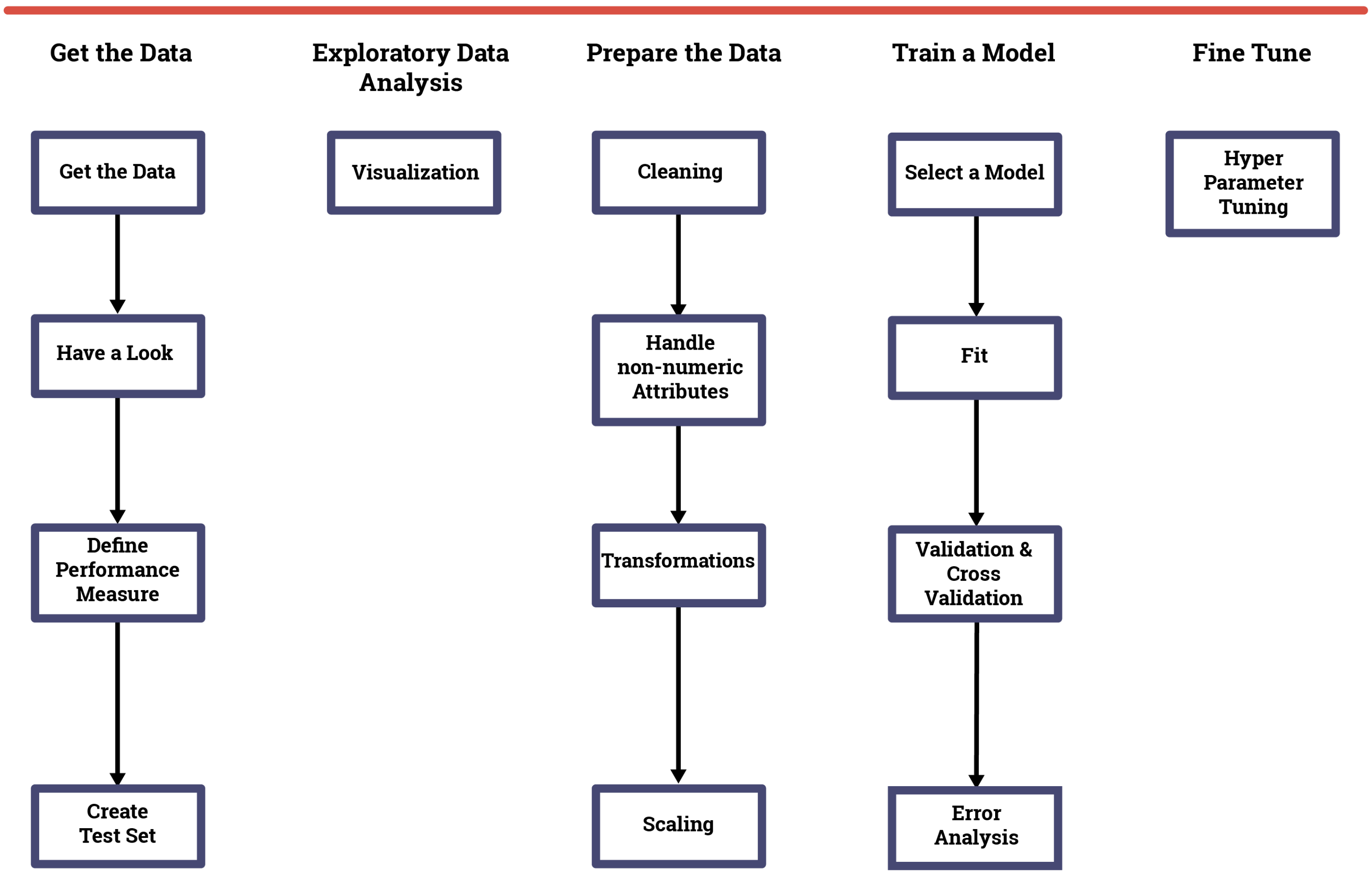
- Defining what "style" is
- What is the best measure of "being close"

but given the framework of the Loss Function, these tasks are closer to Engineering than Art.

Thus, the simple skills we learned

- When applied with discipline (the "Recipe for Machine Learning")
- Can solve seemingly complicated tasks
- Once we have defined a Loss Function embodying our objectives

Recipe for Machine Learning



When these skills are combined with Transfer Learning

- You are truly able to "stand on the shoulder of giants"
- And hopefully solve those tasks that are meaningful to your domain

We look forward to the day when *you* will be the giant on whose shoulders others stand.

In [2]:

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print("Done")
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Done
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