

- Little focus on scalability
 - Pivotal to our predictive theory about visualization interpretability
- Focus on surface-level features
 - Features that do not get at generalizable underlying properties
- Small sample of visualizations
 - Spanning across a single or few domains

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(3) FORM	Color	Dimensions	Animations	Sound	Granularity	Multiple Views	Program Synchronization
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- Debugging usually involves large inputs
- Visualizations must be able to handle significantly large inputs to be effective

Goal: Measure scalability, and thus, effectiveness of program visualizations

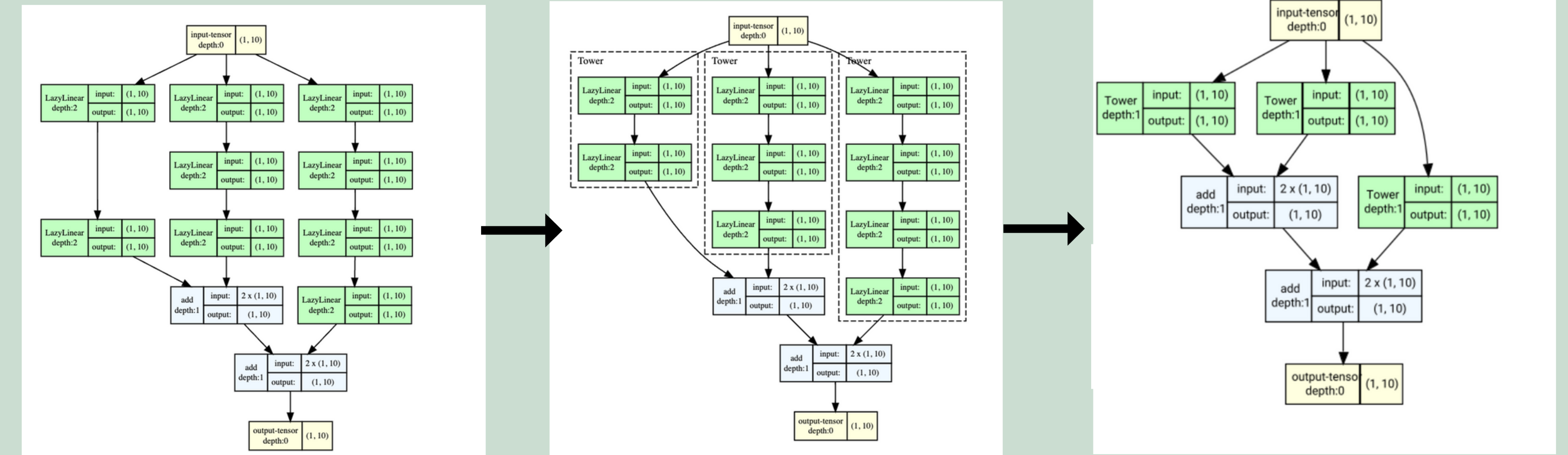
```

graph TD
    Input[Input Image] --> CNN1[Convolutional Neural Network]
    CNN1 --> FeatureMap[Feature Map]
    FeatureMap --> PerturbationDetection[Perturbation Detection Module]
    PerturbationDetection --> PerturbationMap[Perturbation Map]
    PerturbationMap --> ImageRemoval[Remove Adversarial Perturbations]
    ImageRemoval --> CleanImage[Clean Image]
    CleanImage --> CNN2[Convolutional Neural Network]
    CNN2 --> Output[Output Image]
  
```

The flowchart illustrates the proposed method for detecting and removing adversarial perturbations. It begins with an input image, which is processed by a CNN to produce a feature map. This feature map is then processed by a perturbation detection module, which outputs a perturbation map. The perturbation map is used to remove the adversarial perturbations from the input image, resulting in a clean image. The clean image is then processed by a CNN to produce a final output.

Why **doesn't** this visualization **scale well**?

Sliceability: The ease with which the local pieces that make up a visualization can be identified and used to understand the whole structure. The theory aims to understand visualizations as compositions of simpler structures.



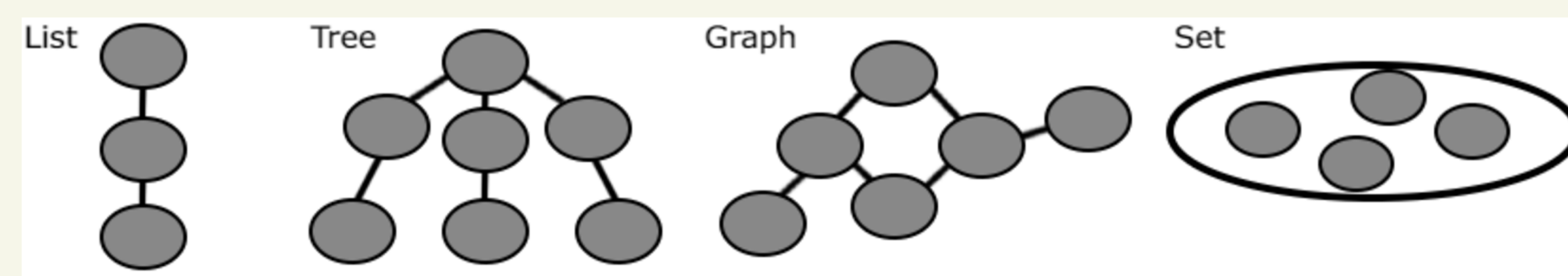
The sliceability of a visualization is an approximate measure of its scalability. Generally, the higher the complexity of an analyzed visualization's structure, the lower the visualization's sliceability and, consequently, the less its scalability.

Develop visualizations' complexity hierarchy and descriptive taxonomy

Use codebook of taxonomy from phase 1 to answer the question: “Are visualizations composed of simpler basic structures more scalable, and thus, more effective?”

Sub-hypothesis: It is possible to group all programming visualizations into a finite number of categories (codebook).

Studied visualizations across 2 levels of abstraction: Literal Visualization and Abstract interpretation.



- **Collected 150 (mechanically generated) examples** across **7 domains**: Machine Learning, Graphics, Web Dev, Game Dev, Video, Animation, and Compilers.
 - Verified they were mechanically generated by looking at their source code
- **Categorically coded** examples as some composition of **4 primary visualization structures**: *sets, lists, trees, and graphs*.
- **Incorporated compositional operators** into our codebook to describe the relationship between parts of a visualization that had different basic structures. These included:
 - Sequential operator (\rightarrow)
 - Parallel operator ($+$)
- Codebook iteratively updated to fit new data until reaching a point of saturation
- Operators allowed to describe the literal visualization and abstract interpretation uniformly, growing them towards each other, thus creating a comprehensive codebook describing both.
 - Examples:

- Examples:

```

215 model_graph = ComputationGraph(
216     visual_graph, input_nodes, show_shapes, expand_nested,
217     hide_inner_tensors, hide_node_names, roll, depth
218 )
219
220 forward_prop(
221     model_graph, input_receiver_tensor, device, model_graph,
222     model_mode, **kwargs_record_tensor
223 )
224
225 model_graph.fill_visual_graph()
226
227 if save_graph:
228     render_graph.visual_graph.render(format='png')
229 return model_graph

```

```

"""fills the graph's graph with desired nodes and edges..."""
self.render_node(nodes)
self.render_edges()
self.render_graph()

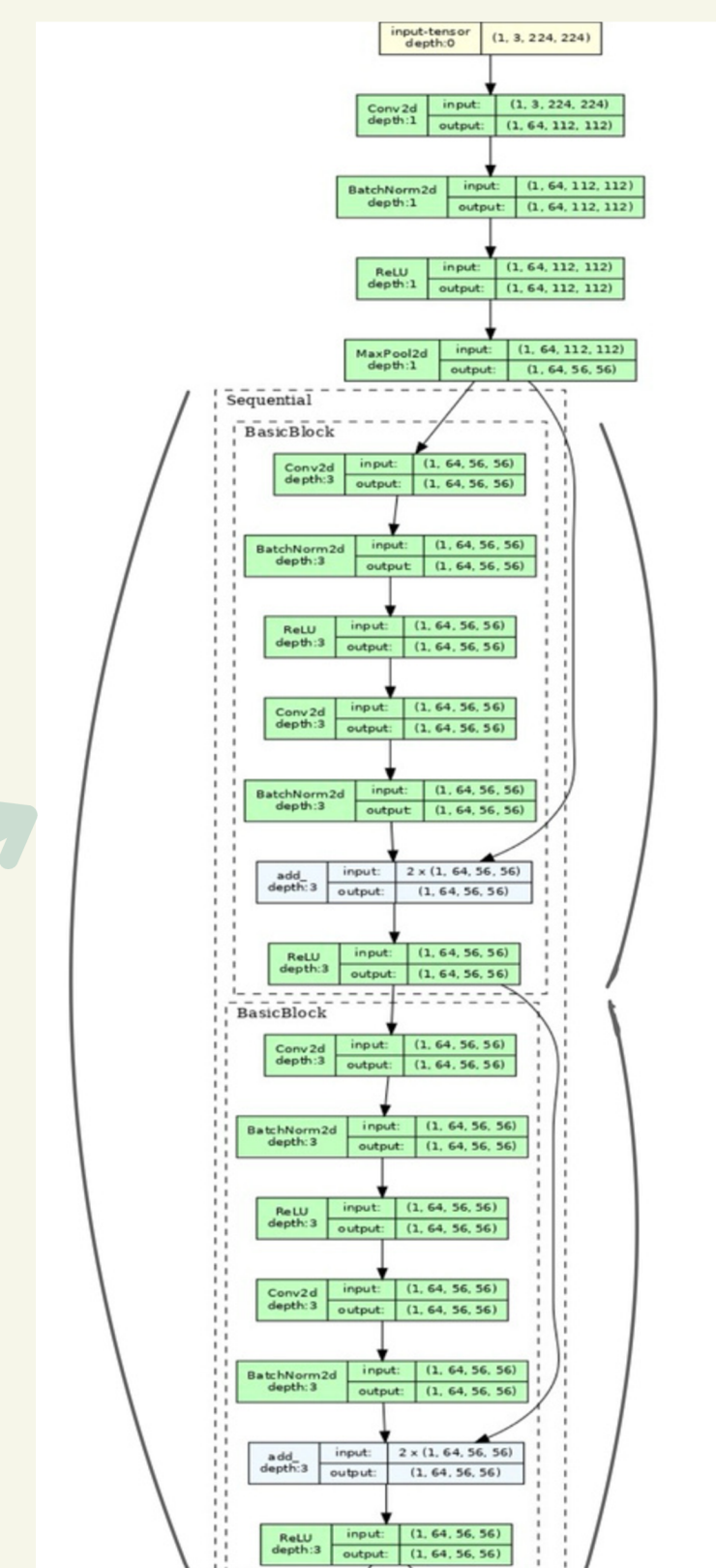
def render_node(nodes):
    """
    Args:
        'var_name': self_node_name,
        'language': None,
    """
    self.render_node(self_node_name, graph=self)

def render_edges(nodes):
    """
    Args:
        graph: all edges in self edge_list to
        be rendered. graph must be the same graph as self
    """
    self.render_edges(nodes, self, self)

def render_graph(nodes):
    """
    Args:
        graph: all edges in self edge_list to
        be rendered. graph must be the same graph as self
    """
    self.render_graph(nodes, self, self)

```

Description: graphviz.Digraph object populated with module hierarchy, torch_functions, shapes, and tensor data recorded during a forward prop. Note: TensorNodes saved in NodeContainer(s): graph



- Codebook got to a level of saturation after 80 examples and could describe every further visualization found
- In many cases, structures composed of simpler primary compositions were preferred when possible--- promising of sliceability
- When used in the restructuring of visualizations, sliceability's predictive power can lend itself to constructive applications:
 - Education
 - Debugging

- Design a game theory experiment to determine if debuggers debug more efficiently with visualizations composed of simpler basic structures
- Interview creators of debugging tools to glean into inherent applications of sliceability employed by same

