Computing Midcurve of a Thin Polygon using Neural Networks

MidcurveNN

Yogesh Haribhau Kulkarni

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Introduction To Midcurve

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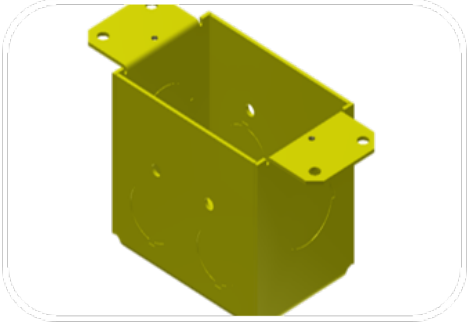
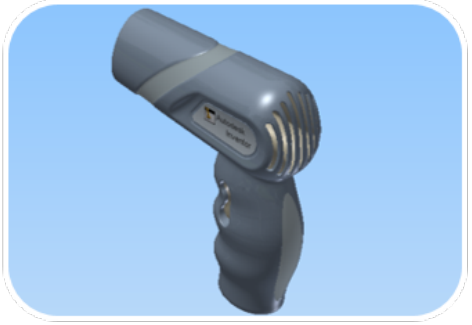
Aerospace

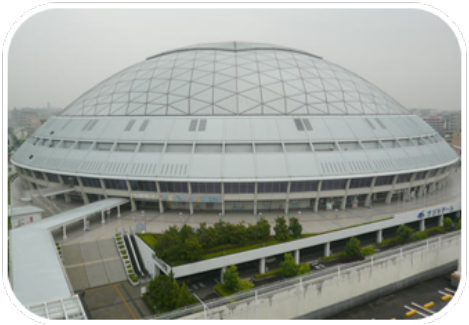


Machinery

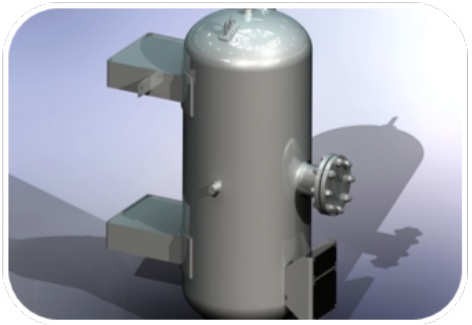


Consumer Products

Energy



Construction



Industrial equipment

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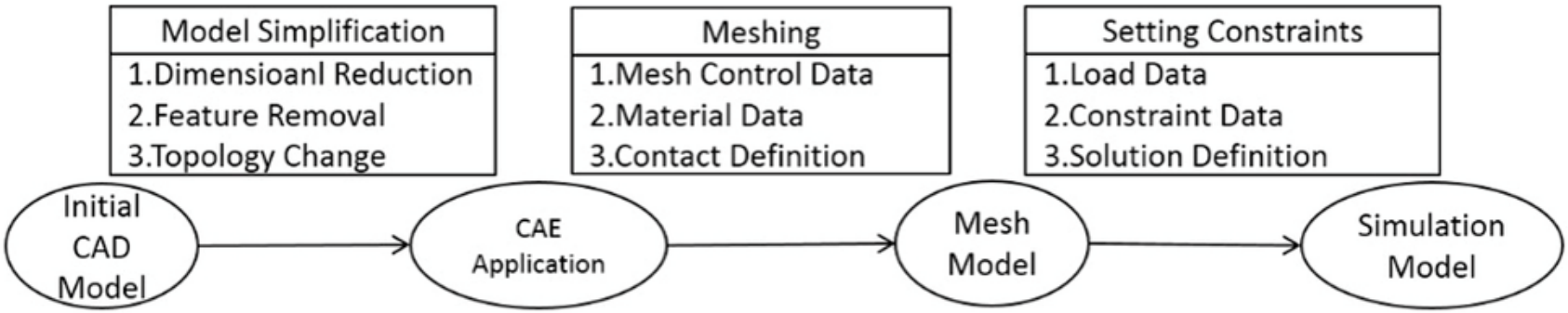
Can we use shapes directly?

- CAD : Designing Shapes
- CAE : Engineering Analysis
- CAD→CAE: Simplification for quicker results.



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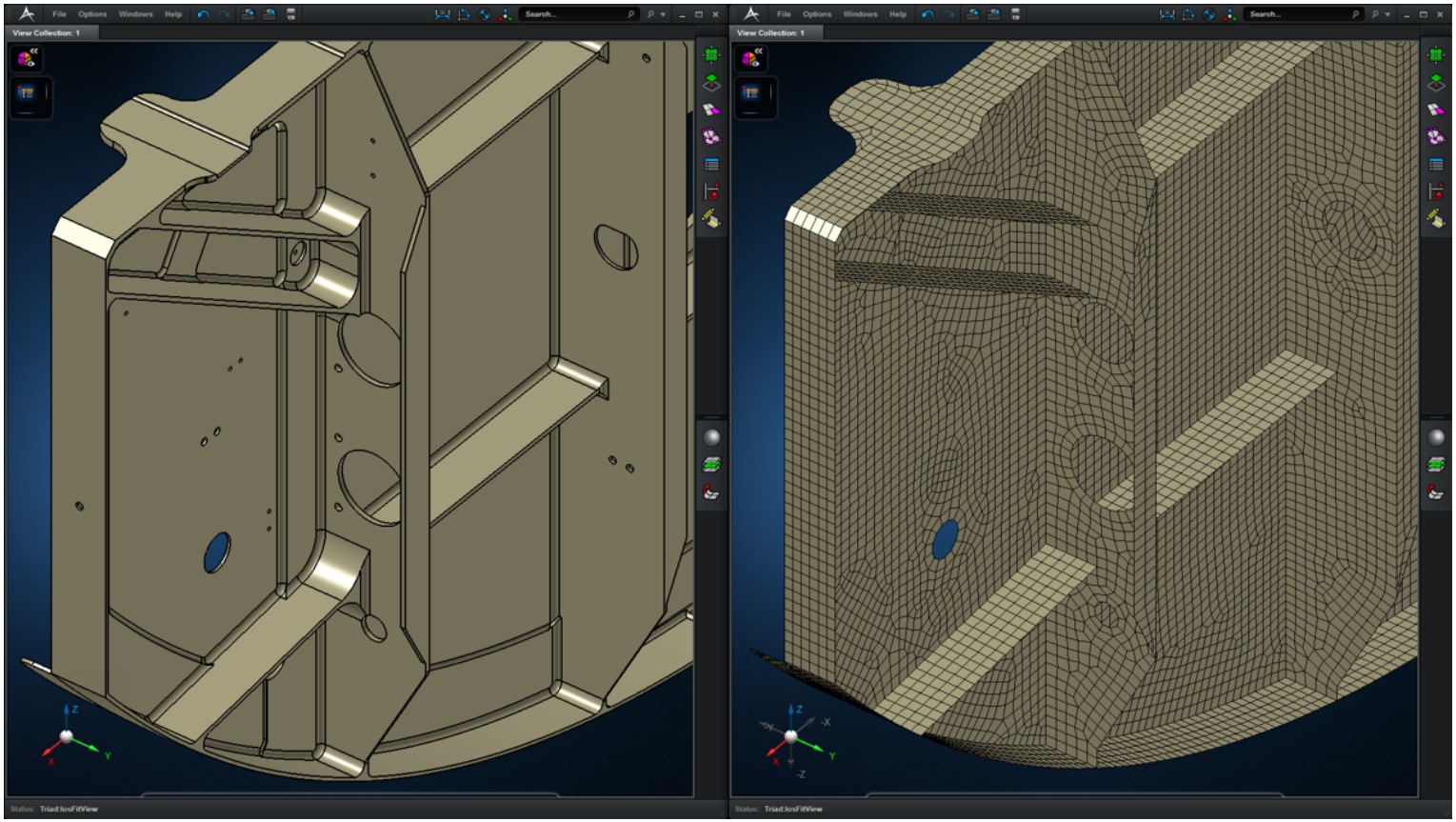
CAD-CAE



For Shapes like Sheet Metal ...

	Solid mesh	Shell+Solid mesh	Difference (%)
Element number	344,330	143,063	-58%
Node Number	694,516	75,941	-89%
Total Degrees of freedom	2,083,548	455,646	-78%
Maximum Von. Mises Stress	**418.4 MPa**	**430 MPa**	+3%
Meshing + Solving time	Out of memory	22 mins	N/A (4G RAM)
Meshing + Solving time	**30 mins**	**17 mins**	-43% (12G RAM)

Half the computation time, but similar accuracy

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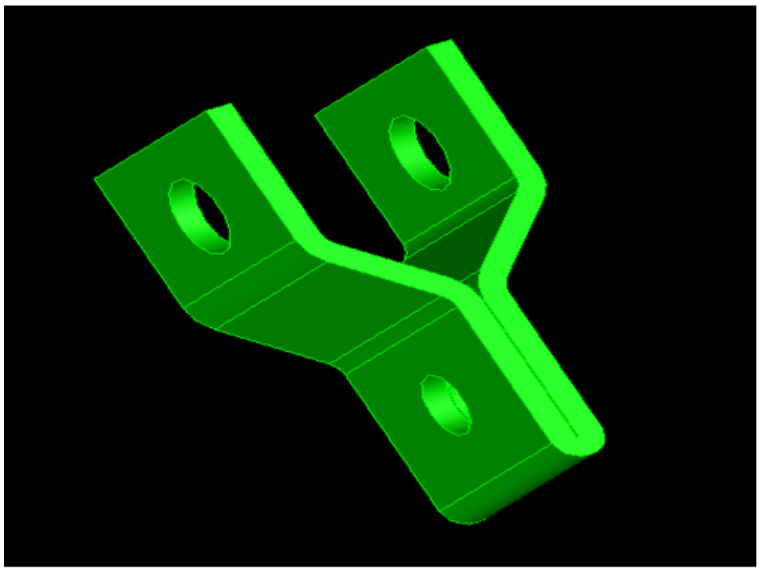
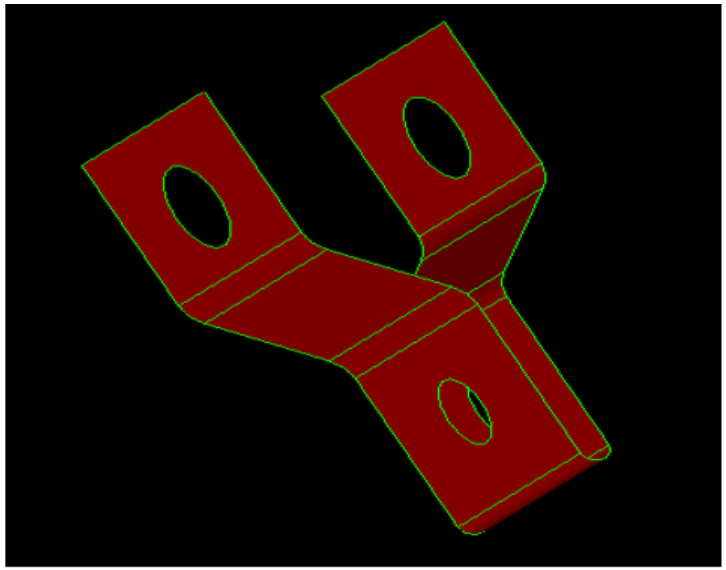
Midsurface is?



Input: Solid



Output: Midsurface

- Widely used for CAE of Thin-Walled parts
- Computation is challenging and still unsolved

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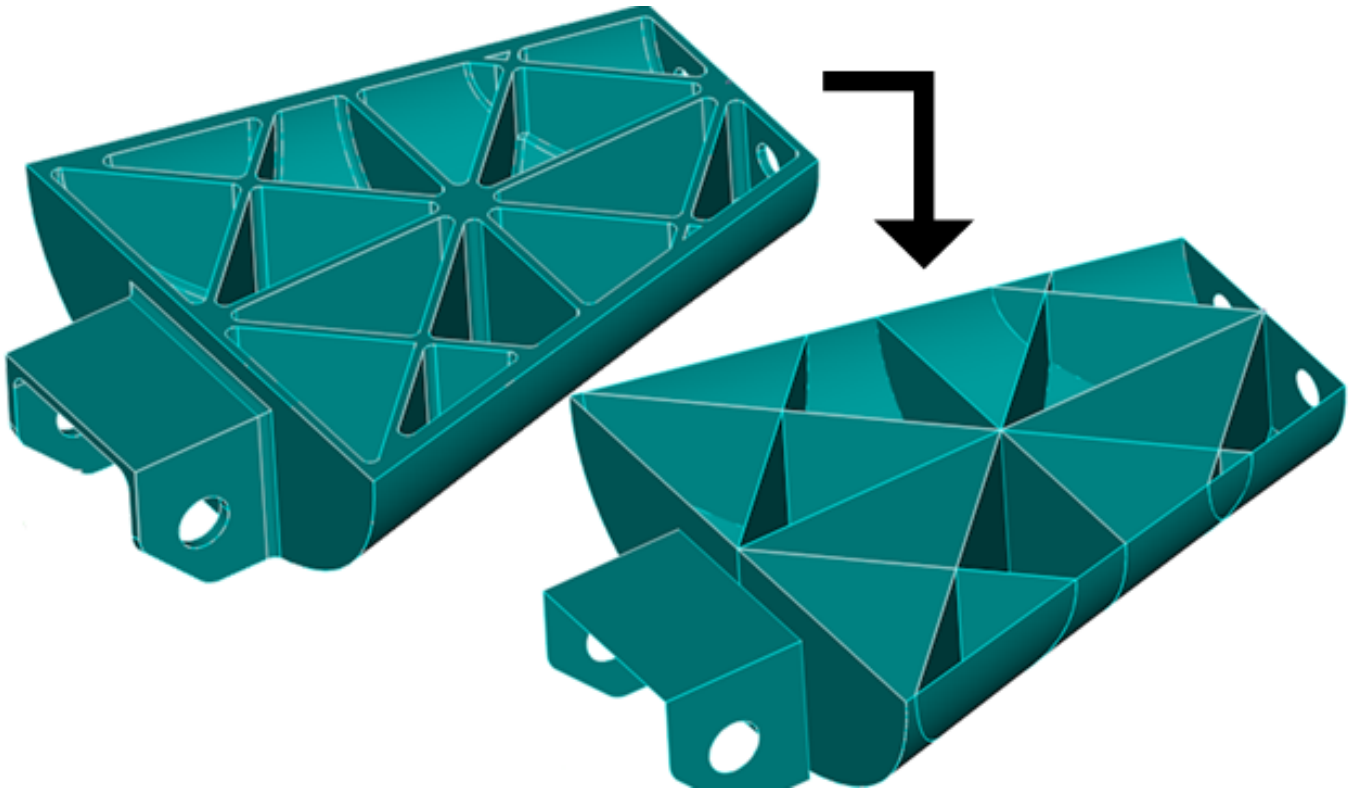
Getting Midsurface

- Going on for decades . . .
- Manually by offsetting and stitching, initially
- Many CAD-CAE packages give automatic option, but . . .



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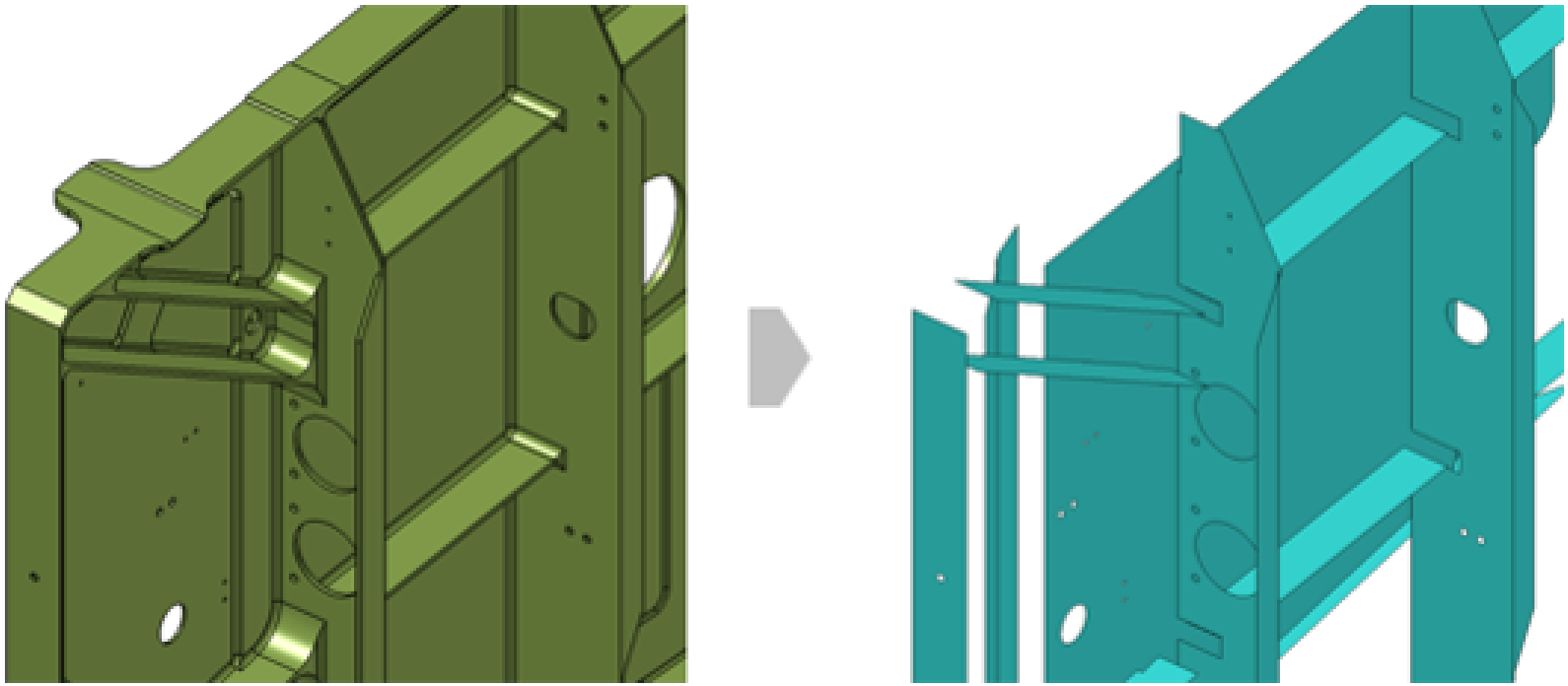
Look at the output



Can't tolerate gaps

- We have thickness sampling,
- To recreate-represent the original shape
- Input and output difference not desirable

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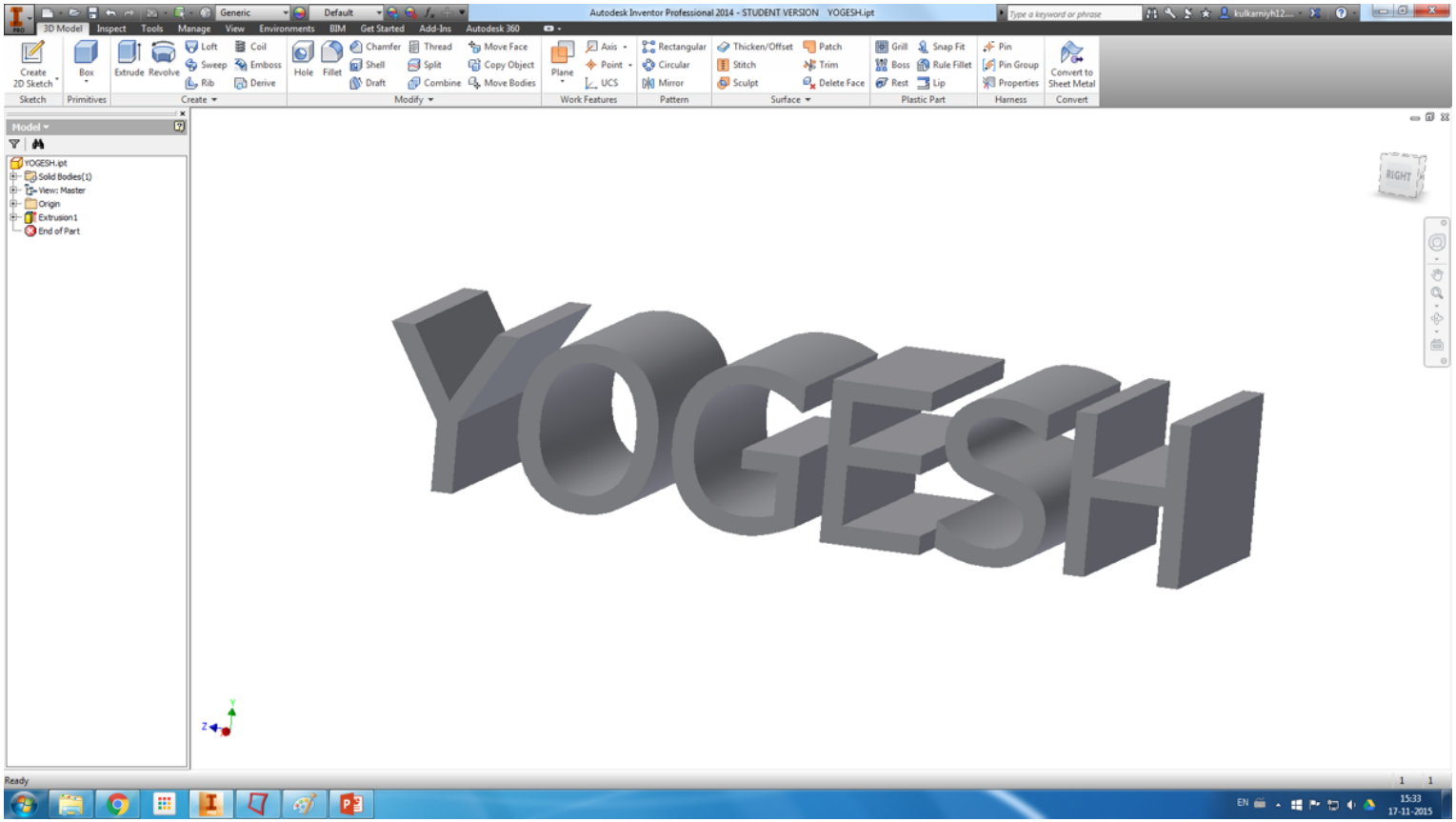
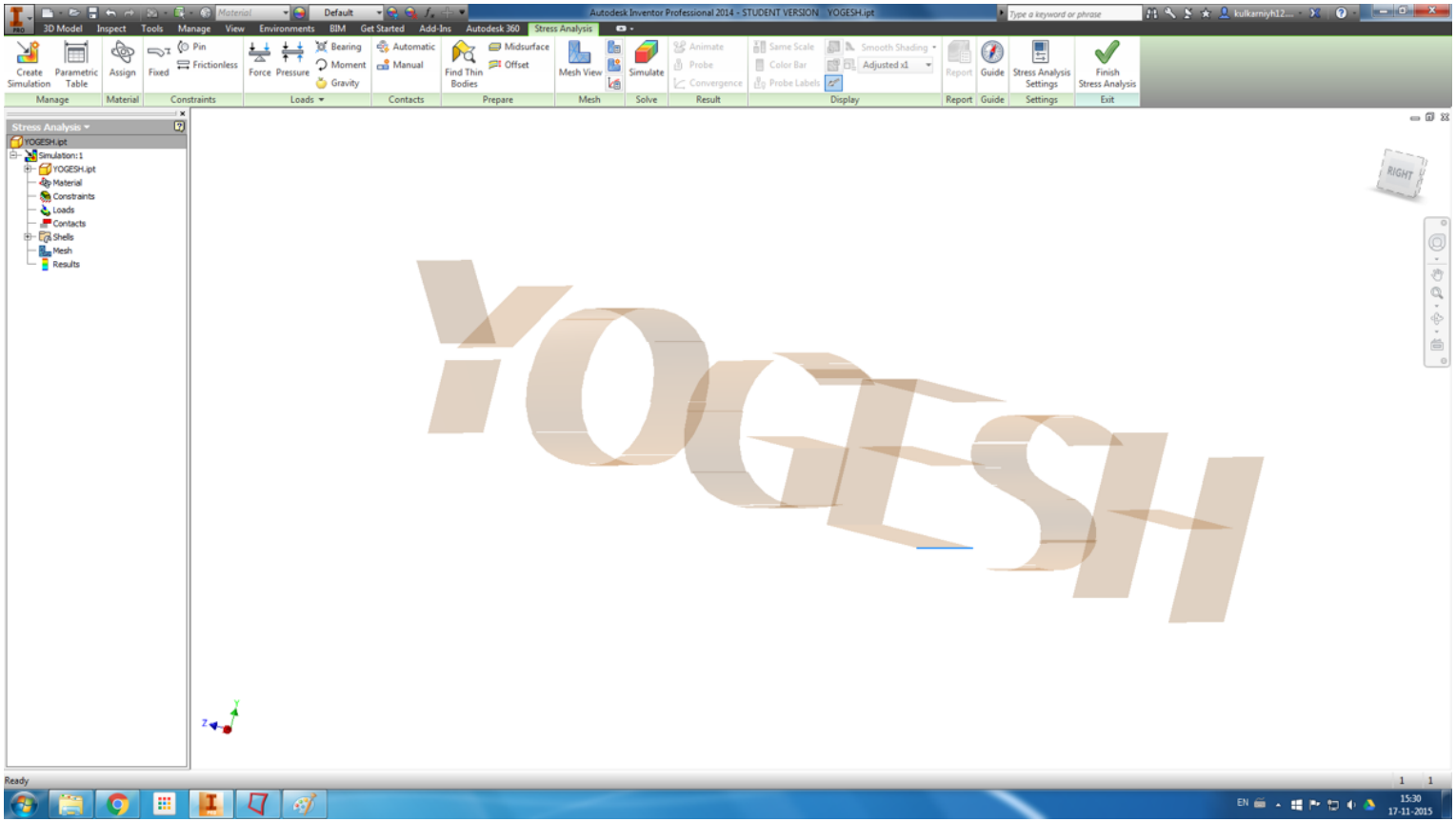
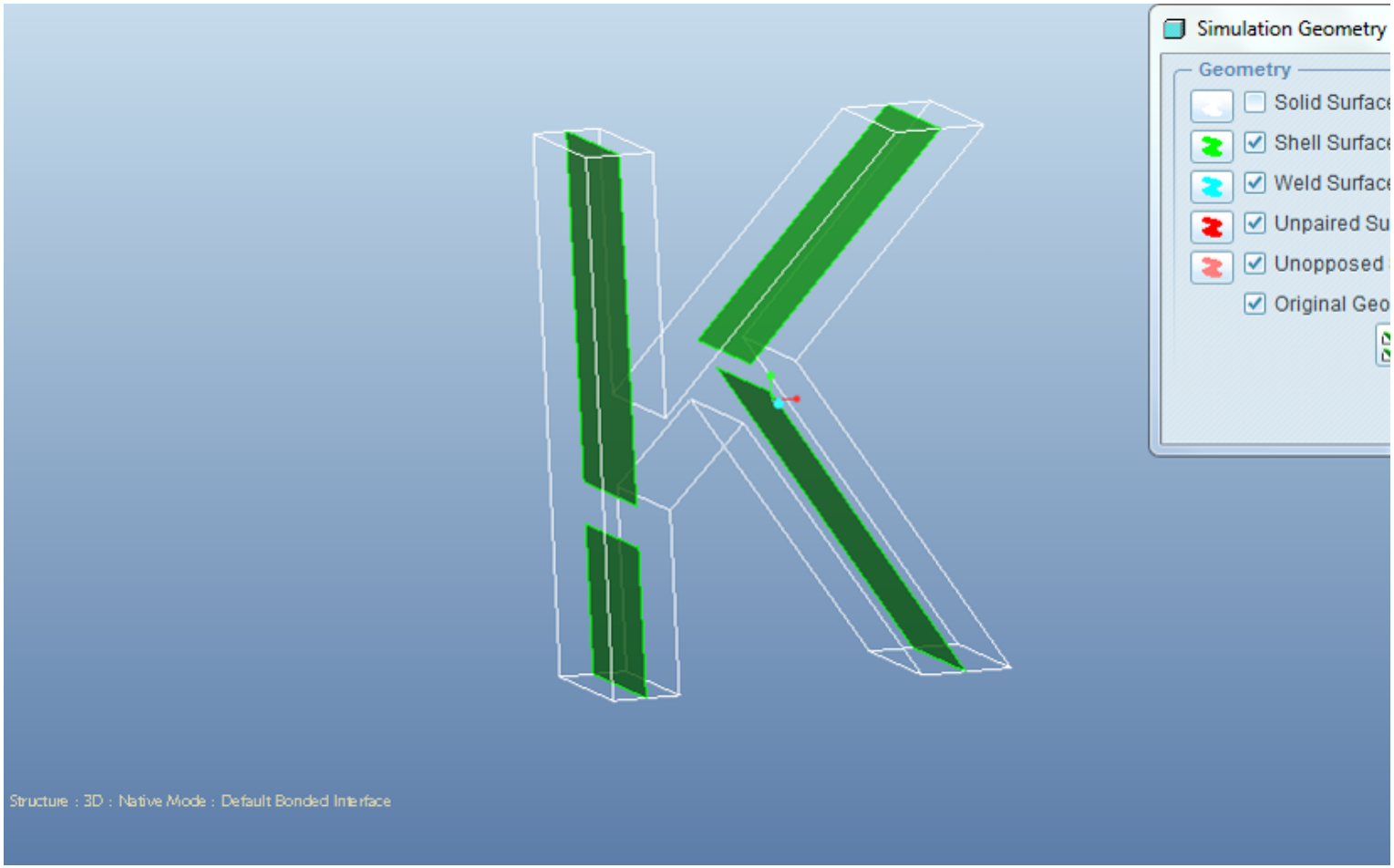
For a simple model like



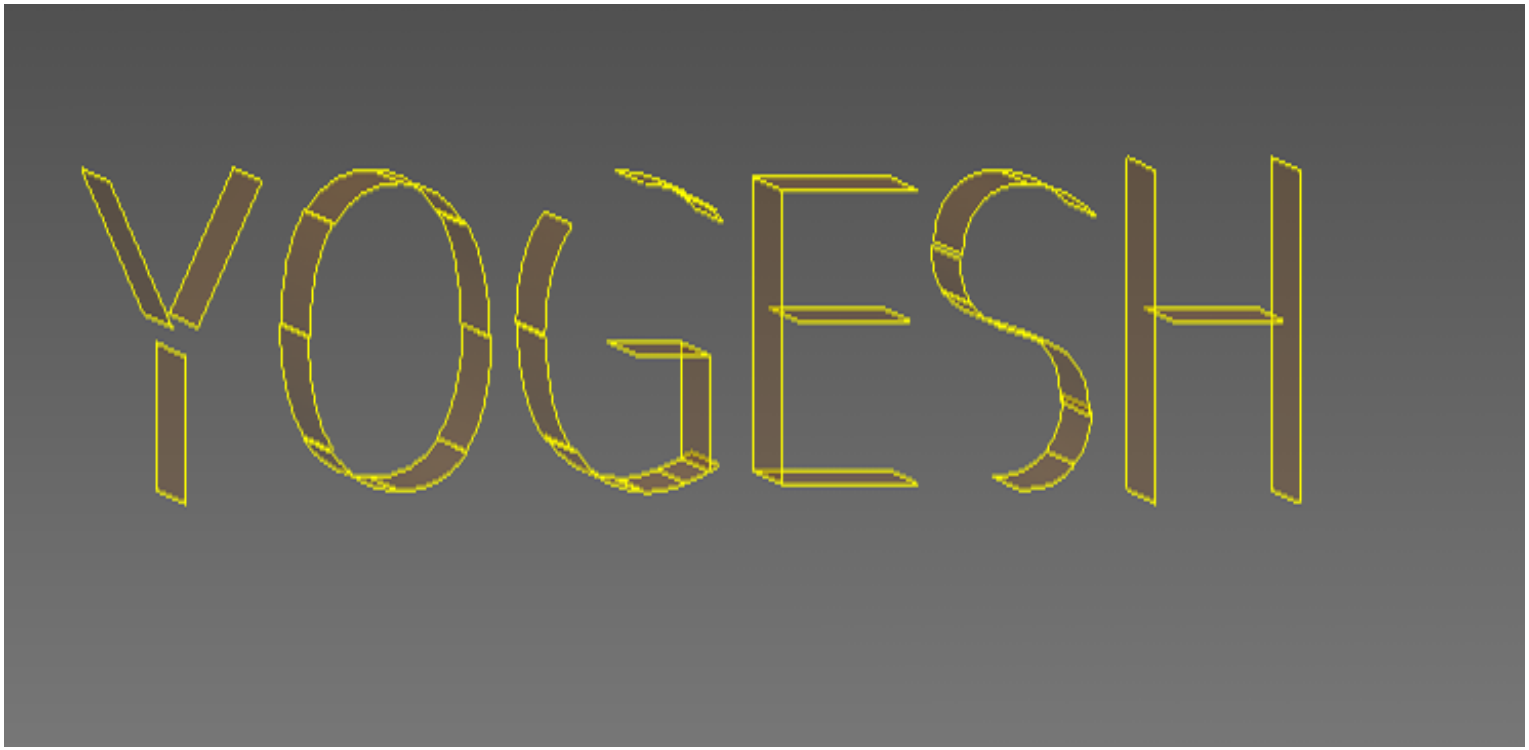
You get


Autodesk Inventor Professional 2014 - STUDENT VERSION YOGESH.ipt
Stress Analysis
YOGESH.ipt
Simulation:1
Material
Constraints
Loads
Contacts
Shells
Mesh
Results
RIGHT
YOGESH
Ready

For a far simpler shape



Current Quality



- Errors take weeks to correct for complex parts.
- But still preferred, due to vast savings time
- From Days to hours . . .

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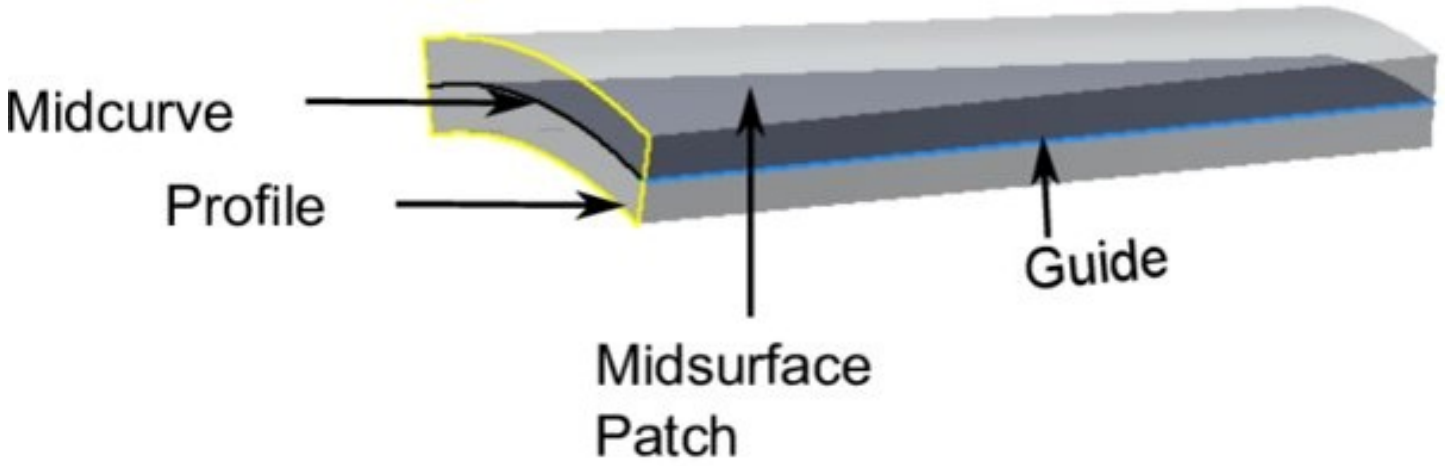
Midsurface Computation

- Midsurface of a Patch is Midcurve of its profile extruded.
- So, it boils down to computing 1D midcurve of a 2D profile



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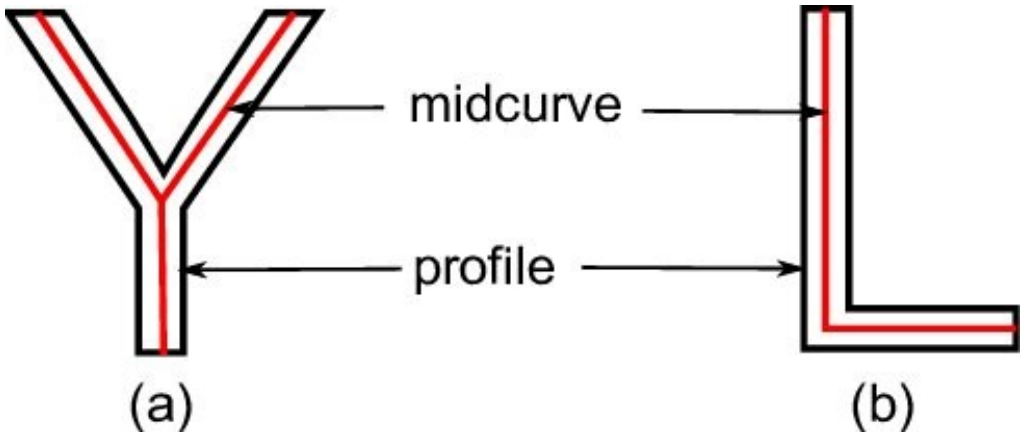
What is a Midcurve?

- Midsurface : From 3D thin Solid to 2D Surface
- Midcurve : From 2D Profile to 1D Curve



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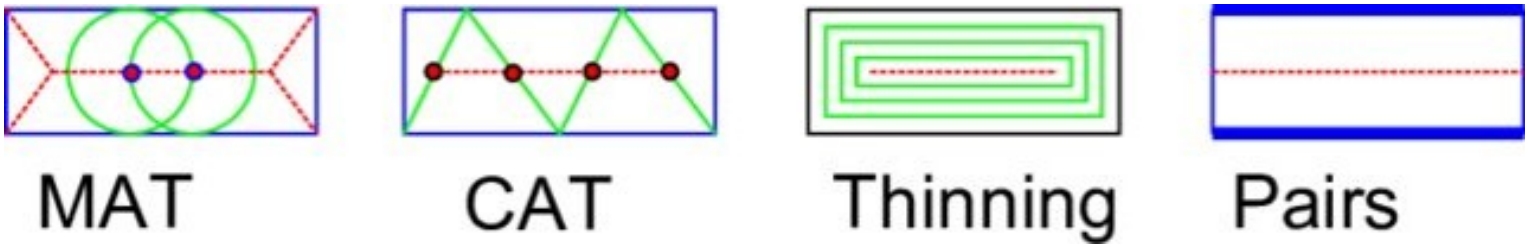
Many Approaches

- More than 6 decades of research...
- Most CAD-CAE packages...
- Rule-based!! Heuristic!! Case-by-case basis!!



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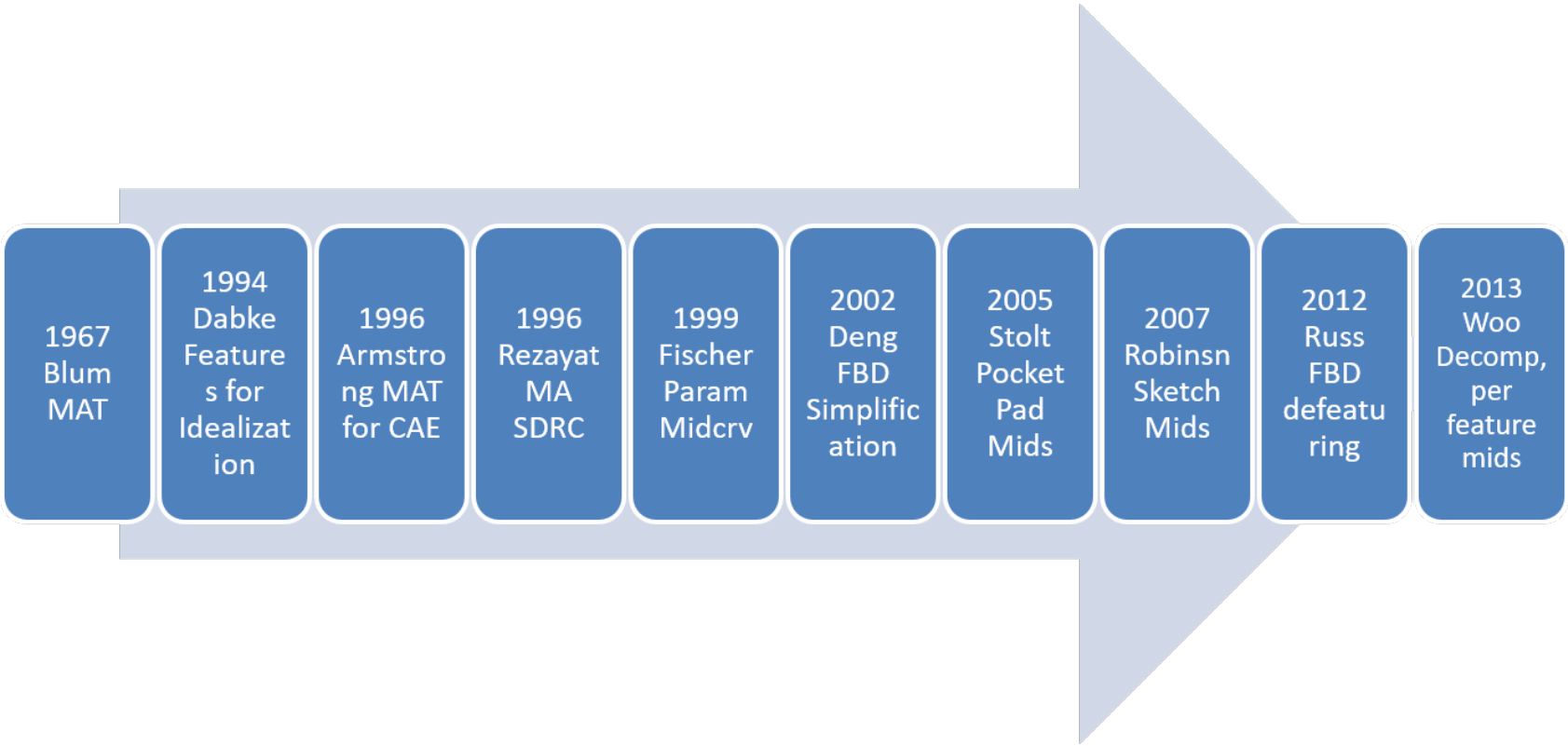
When-What?



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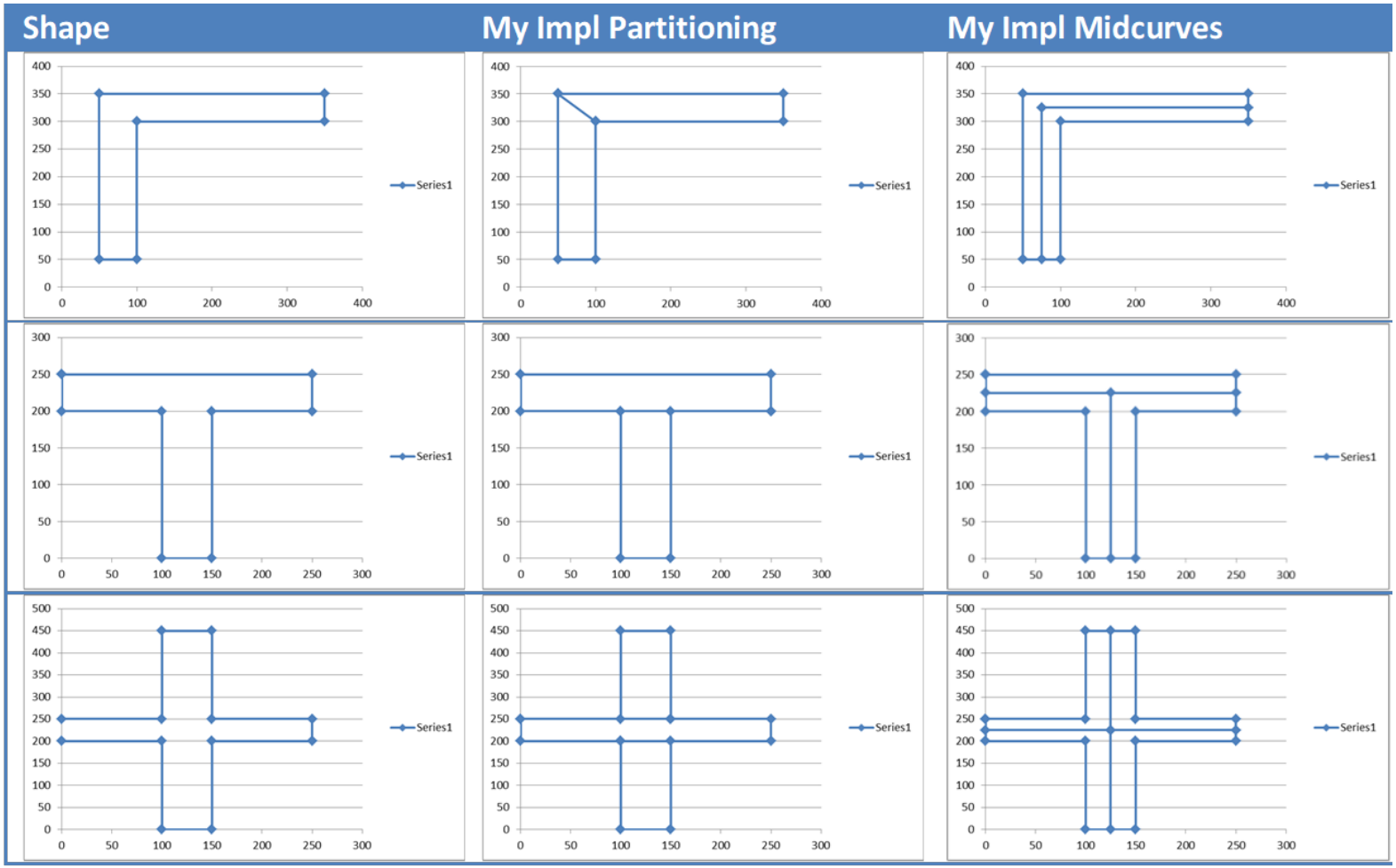
2017: My PhD Work: Rule-based



Limitations

- Fully rule-based
- Need to adjust for new shapes
- So, not scalable

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Idea

Can Neural Networks “learn” the dimension reduction transformation?

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How?

- Supply lots of training data of profiles and their corresponding midcurves and train.
- Then given an unseen profile, can Neural Network compute a midcurve, mimicking the original profile shape?

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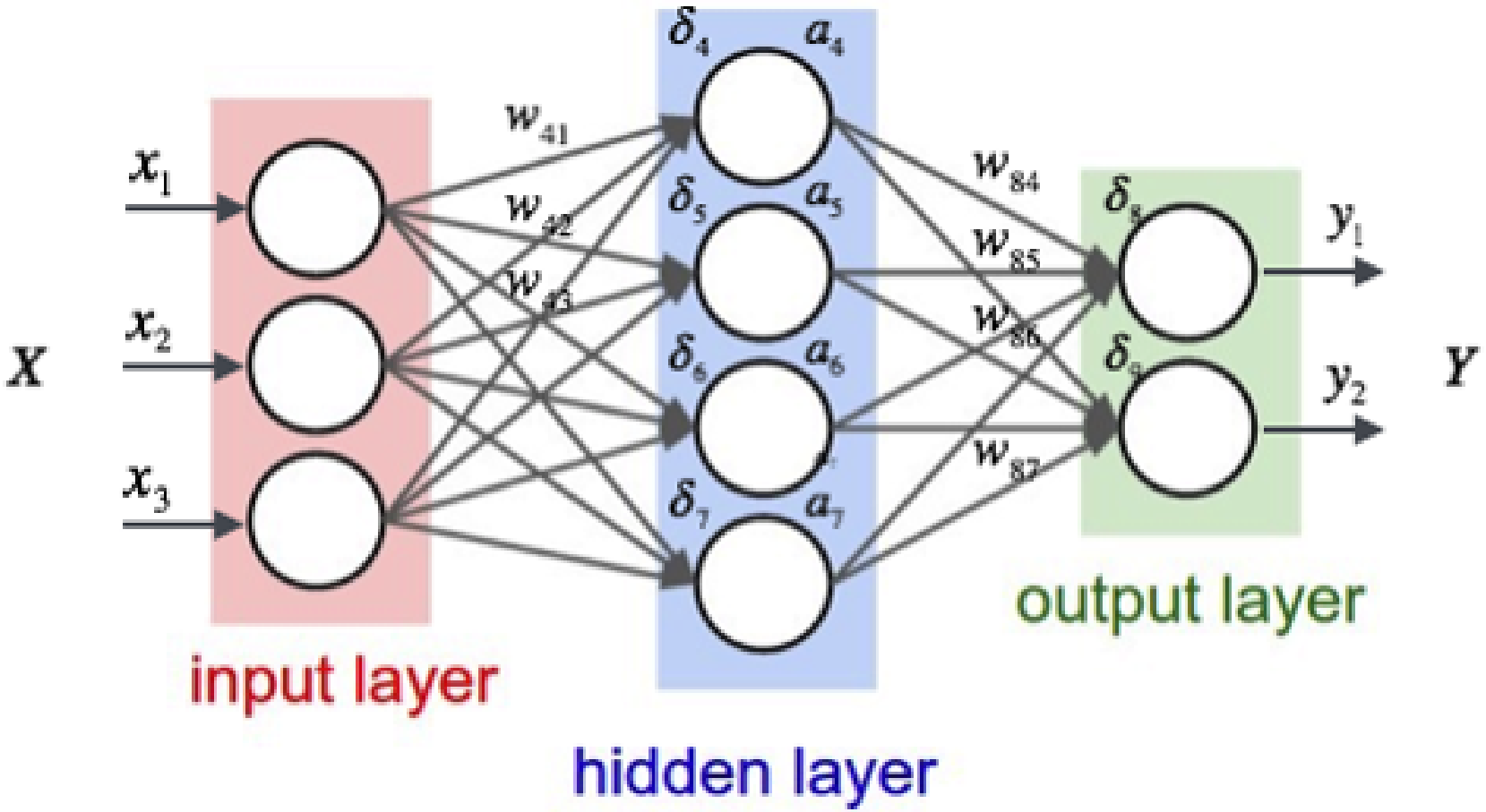
Midcurve by Neural network



Midcurve : The Problem

- **Goal**: Given a 2D closed shape (closed polygon) find its midcurve (polyline, closed or open)
- **Input**: set of points or set of connected lines, non-intersecting, simple, convex, closed polygon
- **Output**: another set of points or set of connected lines, open/branched polygons possible

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Midcurve : Graph 2 Graph

- **Input**: Graph of Input profile with vertices at nodes and lines/curves as edges
- **Output**: another Graph of Output profile with vertices at nodes and lines/curves as edges, open/branched polygons possible
- Both, input and output shapes have different topologies (number of nodes and edges are different) but geometry also, nodes and edges have different positions and shapes. So its network 2 network problem.
- Exiting Graph algorithms like node prediction and link prediction are not useful here as, there, topology of input and output is more or less similar.
- Graph to Graph translation does not seem to evolved enough to do the expected transformation.

Any ideas?

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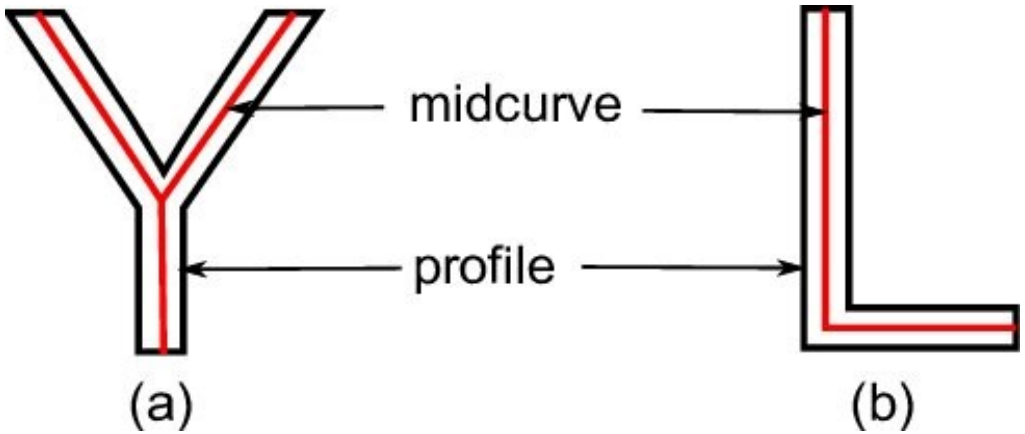
Midcurve == Dimension Reduction

- Like PCA (Principal Component Analysis), wish to find Principal curve
- That 'represents' the original profile shape



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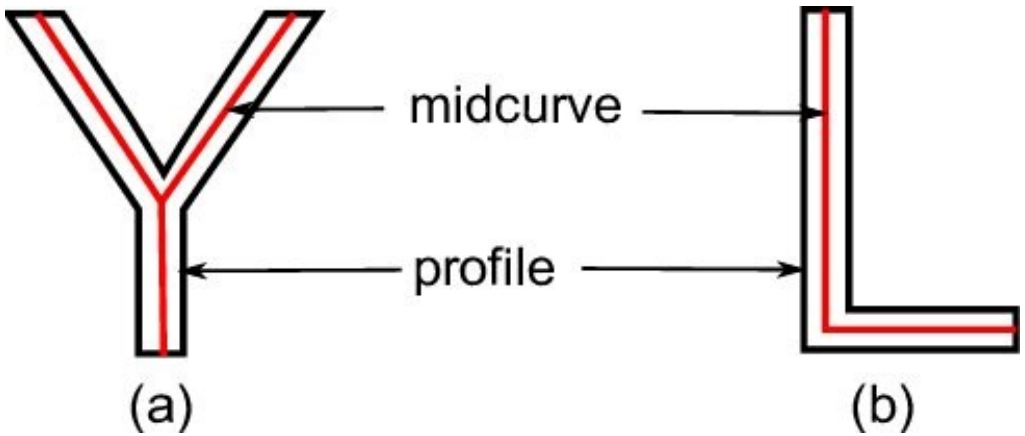
Midcurve == Translation

- Left side (input): 2D Sketch Profile
- Right Side (output): 1D Midcurve
- Sequence 2 Sequence problem



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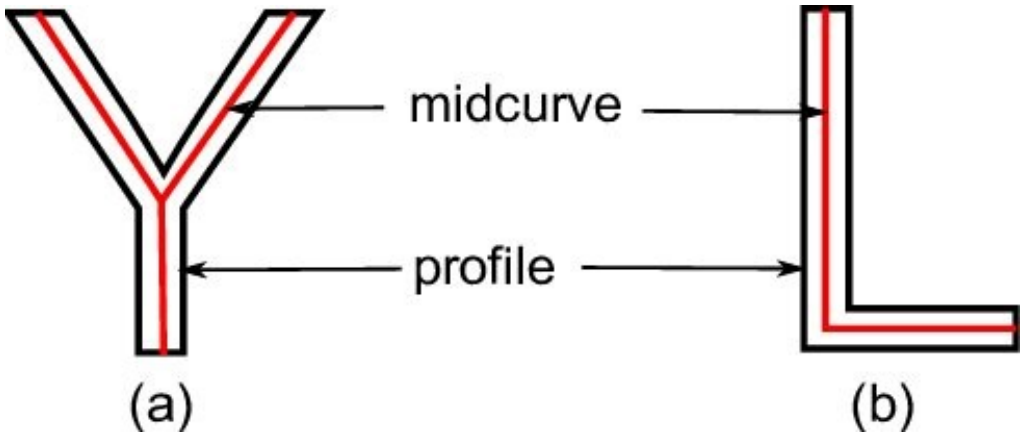
Midcurve ! = Auto-Encoder Decoder

- Its not Auto-Encoder as Input and Output are different
- Its not fixed size i/o as Input and Output sizes are different



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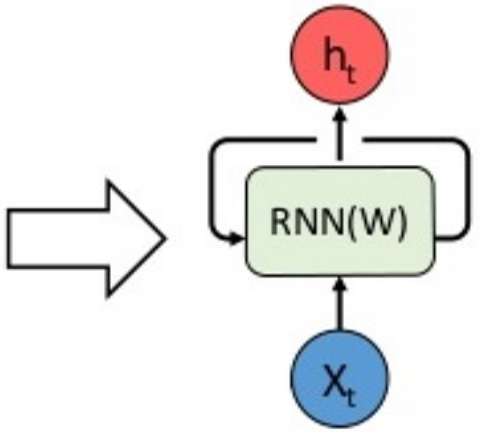
Variable Size Encoder Decoder

- Batches need fixed lengths
- Made fixed size by Padding.

Friendly	against	Scotland	at	Murray	.
Nadim	Ladki	<PAD>	<PAD>	<PAD>	<PAD>
AL-AIN	United	Arab	Emirates	<PAD>	<PAD>
ROME	1996-12	<PAD>	<PAD>	<PAD>	<PAD>
Two	goals	in	the	last	minutes



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Variable Size Encoder Decoder

- OK for NLP, say Machine Translations, where padding values like "-1" can be added along with other words (vectors or indices)
- But in Geometry, its not OK.
- Because any value can represent a Valid Input, even though we don't want it to be the input.

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A Twist to the problem

- Till we get good variable size encoder decoder network for geometry. . .
- Decided to convert this Sequence 2 Sequence problem as Image 2 Image problem.

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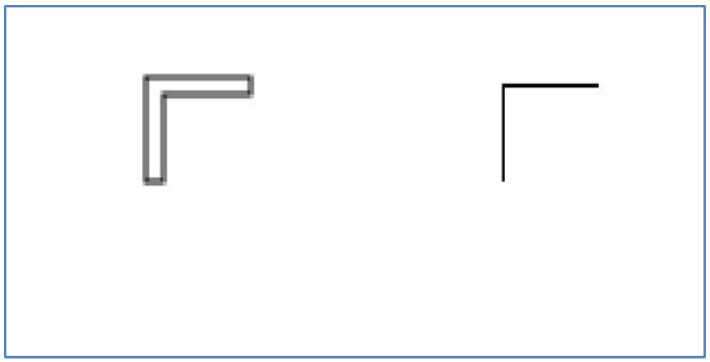
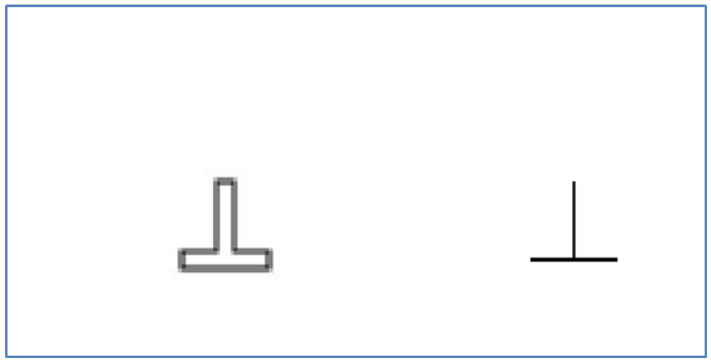
A Twist to the problem

- Input: Black & White Image of 2D profile
- Output: Black & White Image of 1D midcurve





Solves . . .

Problems of Geometric sequences

- Variable input/output sizes
- Loops need to be crossed
- Branches

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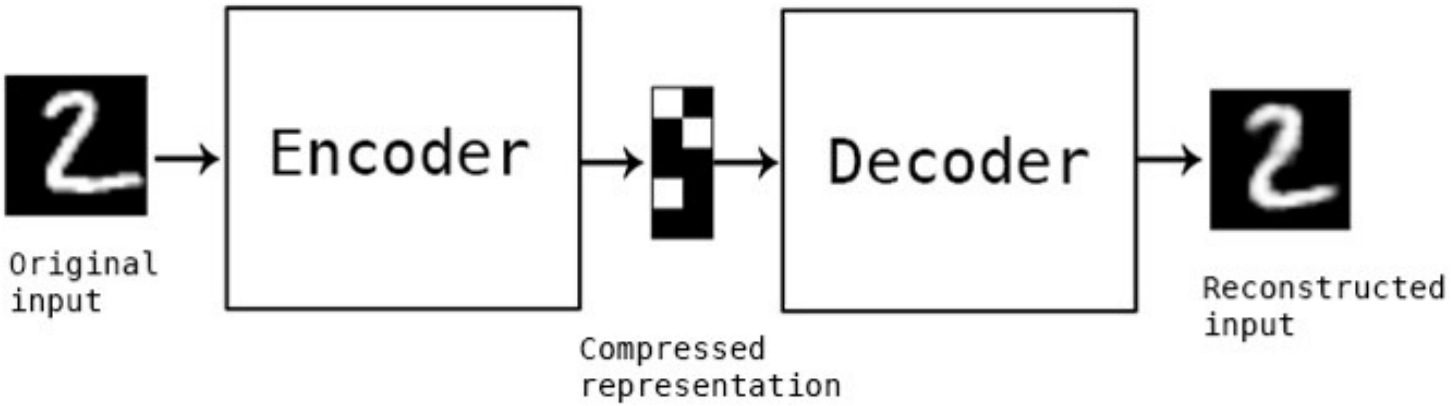
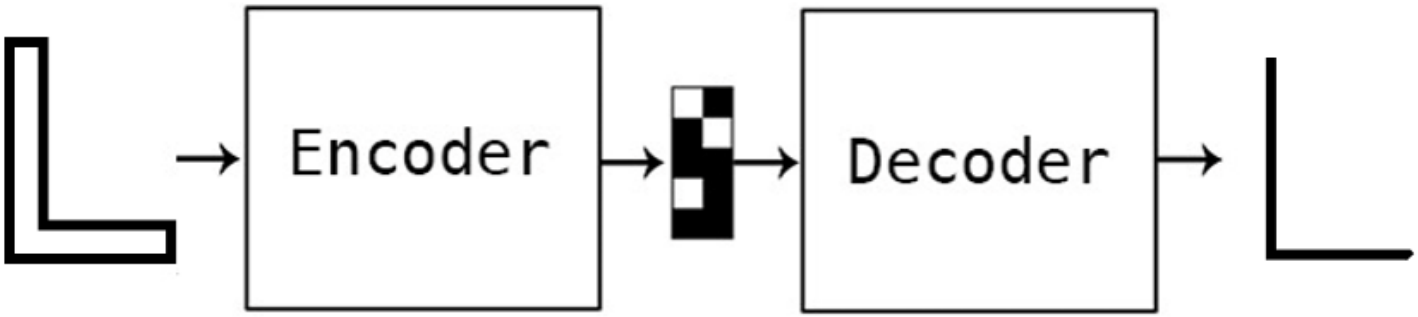
Reuse Image Encoder Decoder



For Dimension Reduction



For Deep Learning

- Need lots of data
- Had just few input output image pairs
- How to augment/populate large variations . . .

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Phase I

Image to Image Transformation Learning:

- Img2Img: This phase focuses on learning image-to-image transformation using fixed-size 100×100 bitmaps.
- Data Augmentation: The training data will be augmented by scaling, rotating, and translating both input and output shapes within the fixed size.
- Network Architecture: An Encoder-Decoder network, specifically Semantic Segmentation or Pix2Pix, will be employed for image-based dimension reduction.

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Data Preparation

Data

Original input and output are in the form of polylines, meaning a list of points, each having x,y coordinates

Profile Data		Profile Picture	Midcurve Data		Midcurve Picture
5.0	5.0		7.5	5.0	
10.0	5.0		7.5	32.5	
10.0	30.0		35.0	32.5	
35.0	30.0		7.5	32.5	
35.0	35.0				
5.0	35.0				

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Data

Profile Data		Profile Picture	Midcurve Data		Midcurve Picture
0	25.0		12.5	0	
25.0	25.0		12.5	22.5	
25.0	20.0		25.0	22.5	
15.0	20.0		0	22.5	
15.0	0				
10.0	0				
10.0	20.0				
0	20.0				

- For each shape, we have this pair of input and output. That's it.
- We need to start with these few samples only

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Augmentation

- Such few profile shapes, are just not enough for Neural Networks to train.
- Need more with as much diversity as possible.
- Will need to artificially augment data with transformations, like pan, rotate, mirror, etc.
- All needs to be automatically, programmatically

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Geometry to Image

- Raw input data is in the Vector format
- Converted it to fixed size (100x100) image by rasterization of drawSVG library.

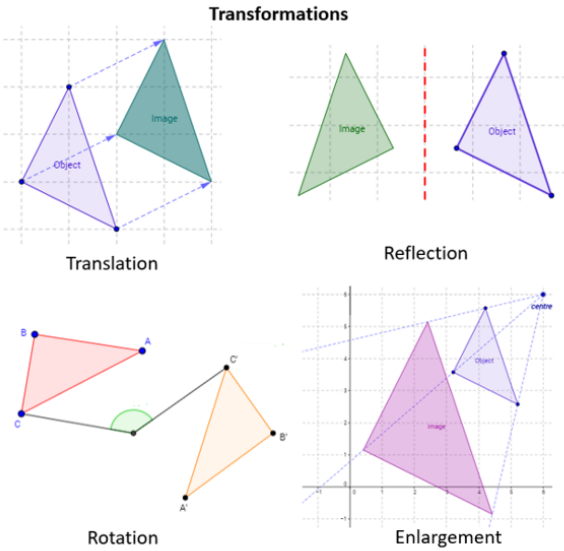
Vector format
.svg

6KB

Raster format
.jpeg .gif .png

12KB

Variations



- Inputs: I, L, Plus, T
- Operations:
  - Translated
  - Rotated
  - Mirrored
  - Mirrored Translated
  - Mirrored Rotated
- Total: 896 images (still less, but not bad)

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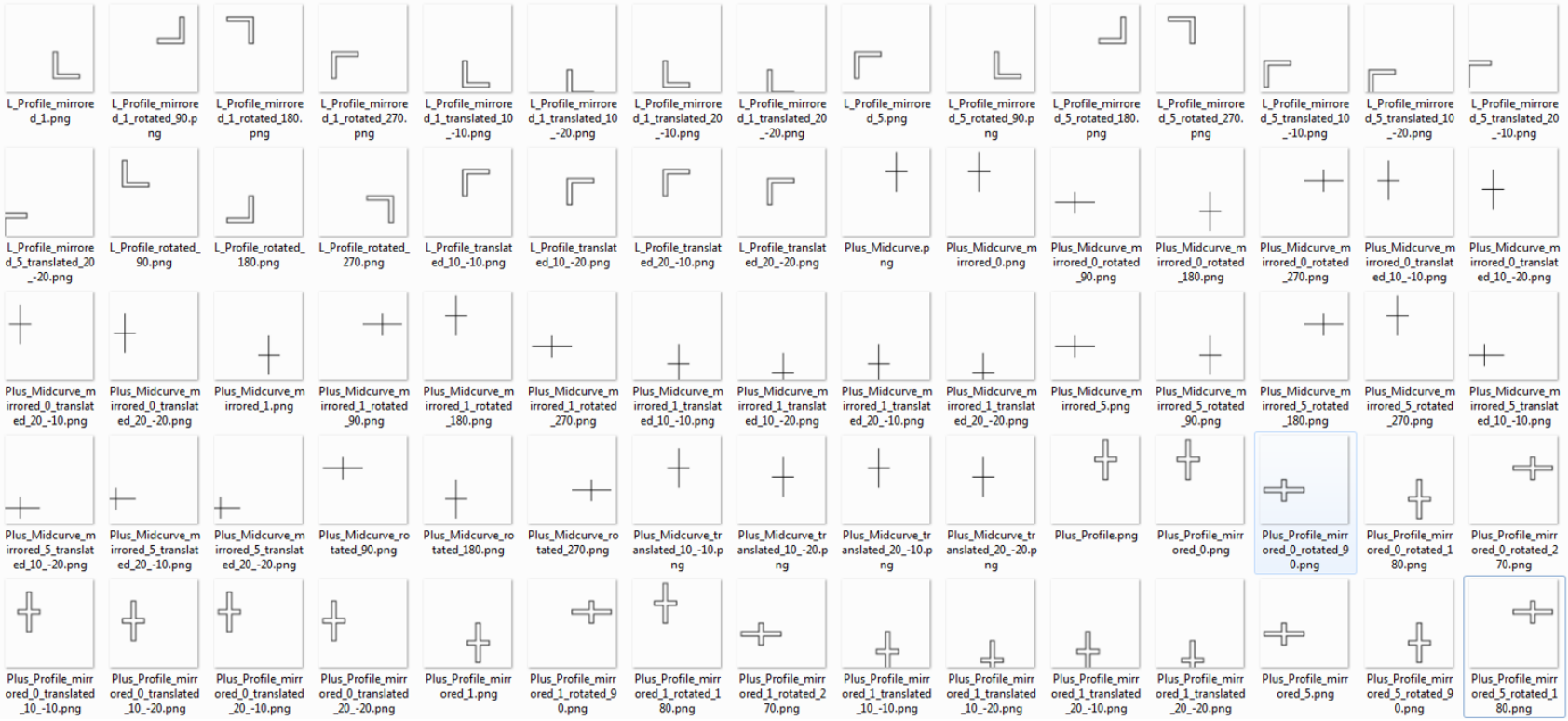
Training Data Samples



Midcurve By Neural Network

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Options For Architectures

- Simple Encoder Decoder (one layer each)
- Dense Encoder Decoder
- Convolutional Encoder Decoder
- Pix2Pix
- ...

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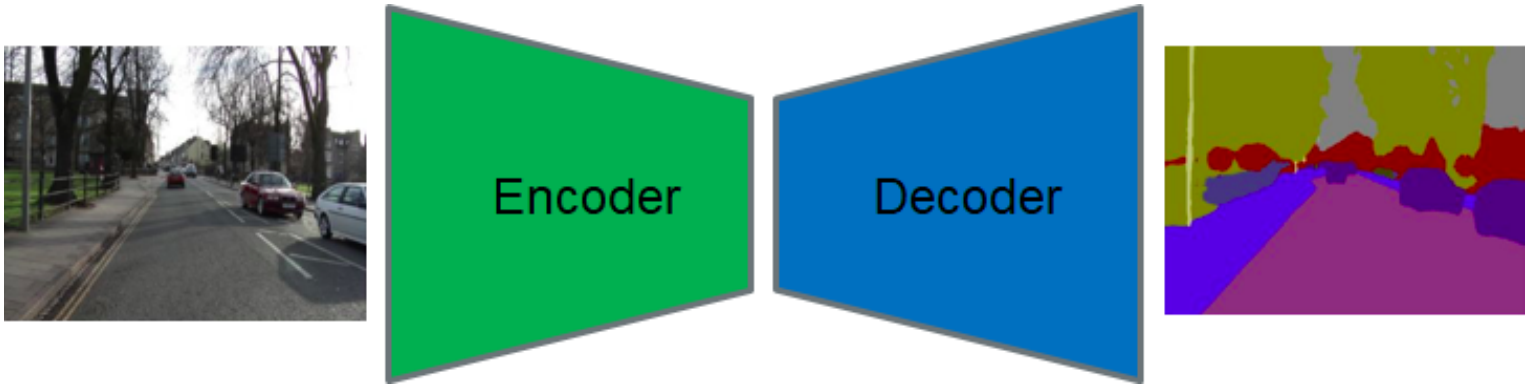
Simple Encoder Decoder

Simple Encoder Decoder



Keras Implementation

```
input_img = Input(shape=(input_dim,))

encoded = Dense(encoding_dim,
     activation='relu',activity_regularizer=regularizers.l1(10e-5))(input_img)
decoded = Dense(input_dim, activation='sigmoid')(encoded)

autoencoder = Model(input_img, decoded)

encoder = Model(input_img, encoded)
encoded_input = Input(shape=(encoding_dim,))
decoder_layer = autoencoder.layers[-1]
decoder = Model(encoded_input, decoder_layer(encoded_input))

autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
```

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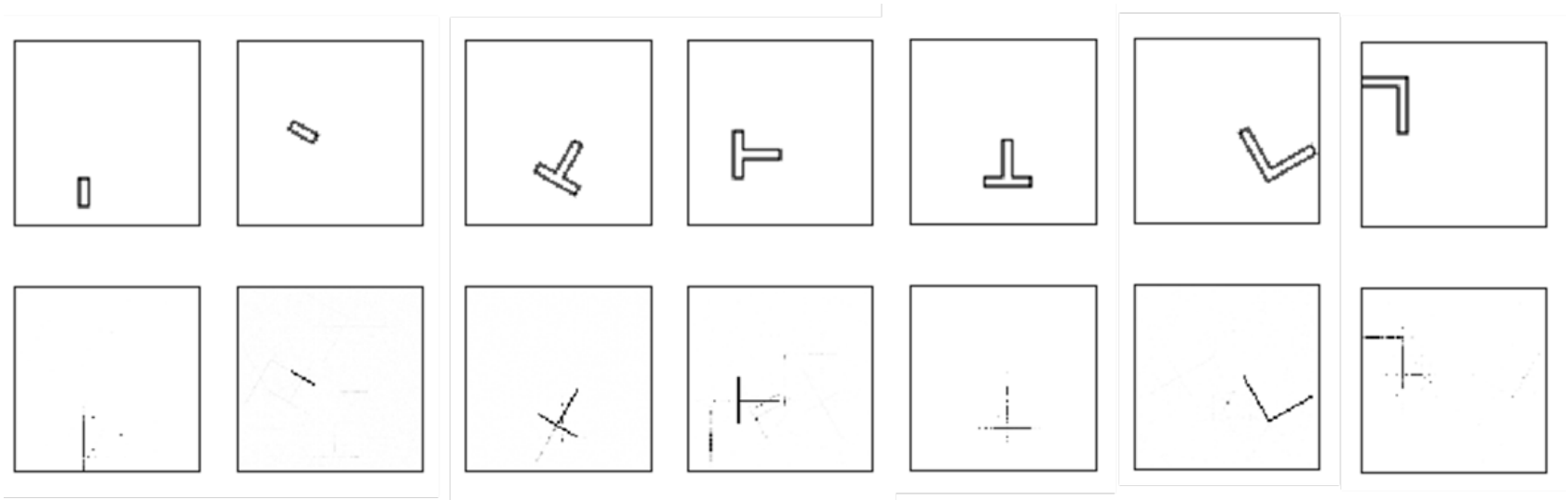
Results



Results

- Not very perfect but encouraging
- NN is correct with
  - The location (bounding box)
  - Dimension Reduction is seen
- But, still some stray points and misses

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What can be done?

- For the noise, use bounding boxes
- Feedback into error term: differencing with the known output expected
- Classify single pixel image as the skeleton, and rest as noise.

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What Next?

- Add denoiser network after the current one
- More Network Architectures
- Sequence-to-Sequence based approaches, taking closed thin polygon as input and polyline as output
- Extending to 3D, ie Midsurface

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Micurve using DNN-CNN

by Prashanth Sreenivasan

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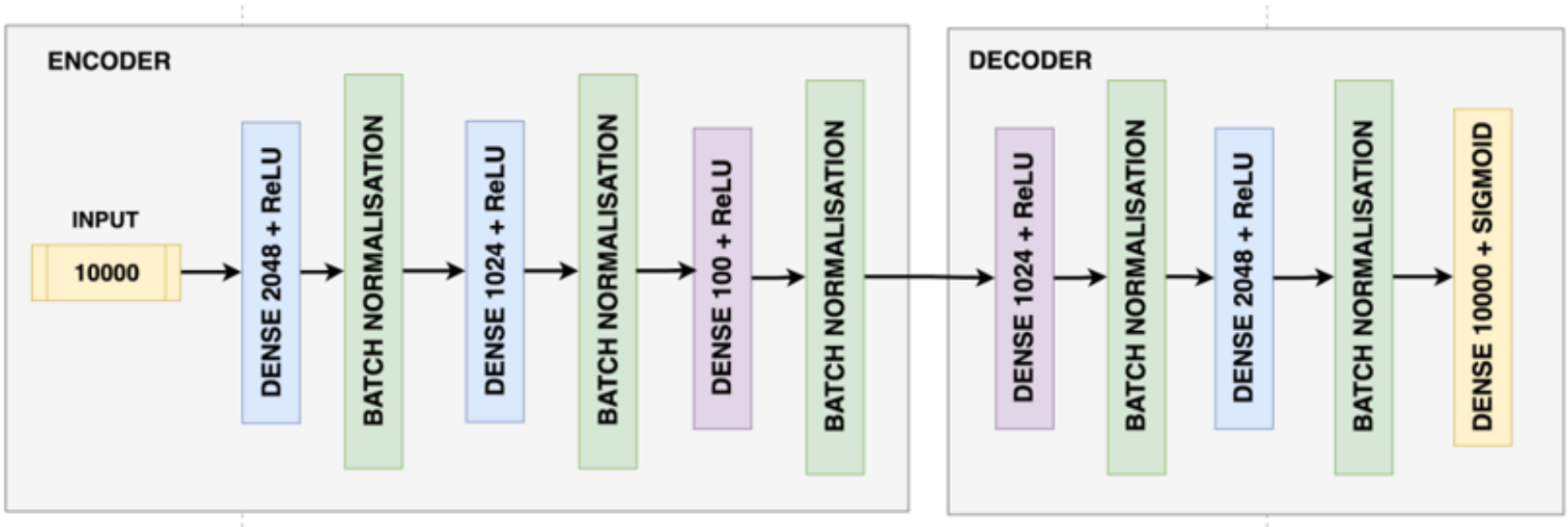
Dense Network Architecture

- Gradual dimension reduction
- Multiple dense layers
- ReLU activation
- Symmetric encoder-decoder



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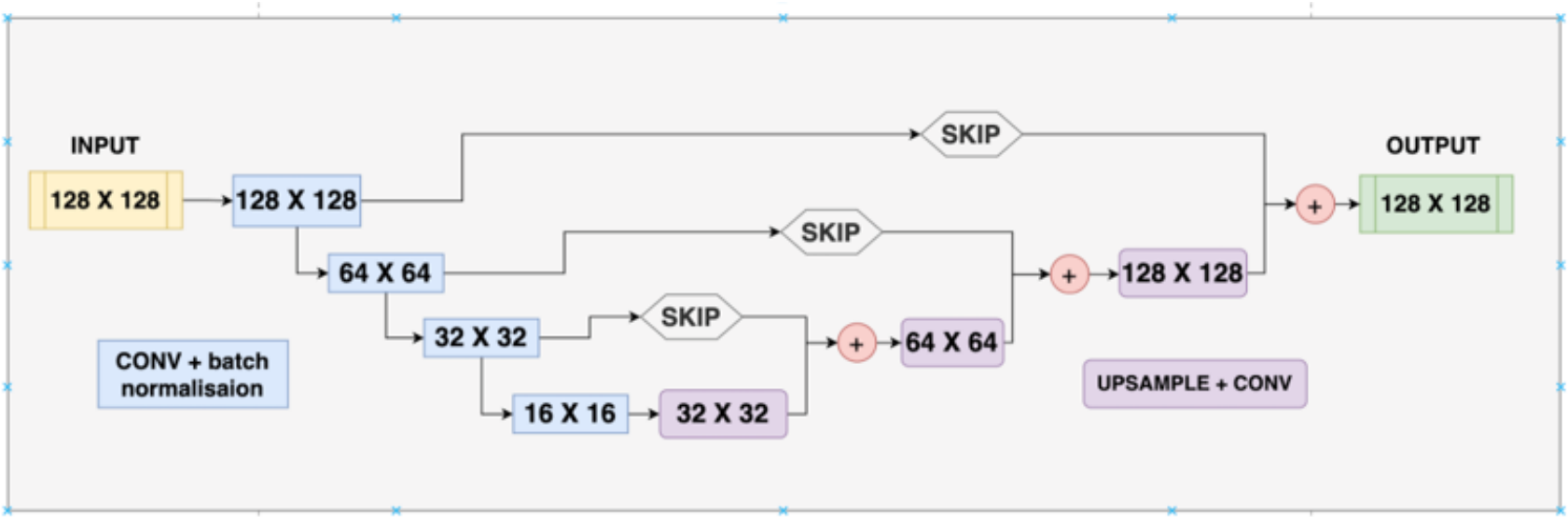
Convolutional Network Architecture

- 4 convolutional blocks
- Skip connections
- Batch normalization
- Dynamic learning rate



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Results

- Performance Metrics
- Comparative Analysis

Metric	Simple	Dense	CNN
Best Epoch	100	62	93
Training Loss	0.0034	0.0049	**0.0003**
Training MAE	0.0023	0.0032	**0.0003**
Validation Loss	0.0080	0.0121	**0.0005**

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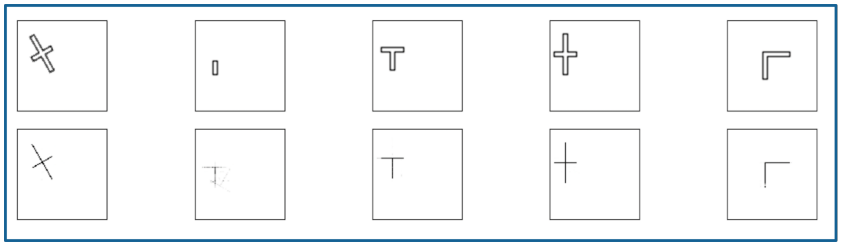
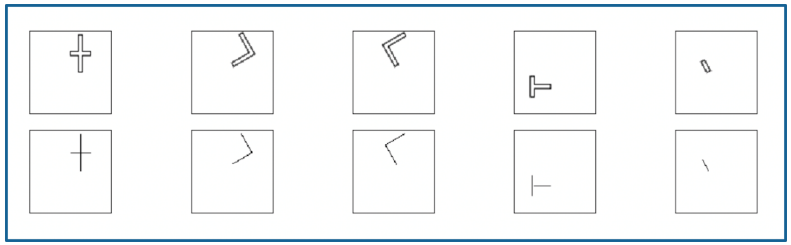
Visual Results

- Input shapes
- Generated Midcurves
- Quality comparison





Conclusions

- CNN architecture performs best
- 10x reduction in loss
- Improved geometric accuracy

YHK

Idea

Can Large Language Models “learn” the dimension reduction transformation?

YHK

LLMs for Midcurve Implementation

Proposed Approach

Text to Text Transformation Learning:

- Geometric Representation: A text-based representation of the geometry/graph/network will be explored to leverage Natural Language Processing (NLP) techniques.
- Existing Methods: The paper (Fatemi, Halcrow, and Bryan 2023) surveys several text-based representations for graph data, but none appear specifically suited for geometric shapes.
- Proposed Approach: A geometry representation similar to 2D Boundary Representation (B-rep) will be utilized, adapting the concept from 3D to 2D.

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Representation of Geometry

- One limitation of 2D geometry-shape, represented as a sequential list of points, is that we can not represent line intersections or concentric loops.
- To address this a more comprehensive structure has been proposed which is based on the corresponding 3D structure popular in Solid Modeling, called Brep (Boundary Representation).

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2D Brep Representation

Leverage a geometry representation similar to that found in 3D B-rep (Boundary representation), but in 2D. It can be shown as:

```
{
 'ShapeName': 'I',
 'Profile': [(5.0, 5.0), (10.0, 5.0), (10.0, 20.0), (5.0, 20.0)],
 'Midcurve': [(7.5, 5.0), (7.5, 20.0)],
 'Profile_brep': {
    'Points': [(5.0, 5.0), (10.0, 5.0), (10.0, 20.0),(5.0, 20.0)], # list of
     (x,y) coordinates
    'Lines': [[0, 1], [1, 2], [2, 3], [3, 0]], # list of point ids (ie index
     in the Points list)
                'Segments': [[0, 1, 2, 3]] # list of line ids (ie index in
     Lines list)
    },
 'Midcurve_brep': {
    'Points': [(7.5, 5.0), (7.5, 20.0)],
    'Lines': [[0, 1]],
                'Segments': [[0]]
    },
}
```

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Data

ShapeName	Profile	Midcurve	Profile_brep	Midcurve_brep
I	[[5.0, 5.0], [10.0, 5.0], [10.0, 20.0], [5.0, 20.0]]	[[7.5, 5.0], [7.5, 20.0]]	{"Points": [[5.0, 5.0], [10.0, 5.0], [10.0, 20.0], [5.0, 20.0]], "Lines": [[0, 1], [1, 2], [2, 3], [3, 0]], "Segments": [[0, 1, 2, 3]]}	{"Points": [[7.5, 5.0], [7.5, 20.0]], "Lines": [[0, 1]], "Segments": [[0]]}
L	[[5.0, 5.0], [10.0, 5.0], [10.0, 30.0], [35.0, 30.0], [35.0, 35.0], [5.0, 35.0]]	[[7.5, 5.0], [7.5, 32.5], [35.0, 32.5]]	{"Points": [[5.0, 5.0], [10.0, 5.0], [10.0, 30.0], [35.0, 30.0], [35.0, 35.0], [5.0, 35.0]], "Lines": [[0, 1], [1, 2], [2, 3], [3, 4], [4, 5], [5, 0]], "Segments": [[0, 1, 2, 3, 4, 5]]}	{"Points": [[7.5, 5.0], [7.5, 32.5], [35.0, 32.5]], "Lines": [[0, 1], [1, 2]], "Segments": [[0, 1]]}
Plus	[[0.0, 25.0], [10.0, 25.0], [10.0, 45.0], [15.0, 45.0], [15.0, 25.0], [25.0, 25.0], [25.0, 20.0], [15.0, 20.0], [15.0, 0.0], [10.0, 0.0], [10.0, 20.0], [0.0, 20.0]]	[[12.5, 0.0], [12.5, 22.5], [12.5, 45.0], [0.0, 22.5], [25.0, 22.5]]	{"Points": [[0.0, 25.0], [10.0, 25.0], [10.0, 45.0], [15.0, 45.0], [15.0, 25.0], [25.0, 25.0], [25.0, 20.0], [15.0, 20.0], [15.0, 0.0], [10.0, 0.0], [10.0, 20.0], [0.0, 20.0]], "Lines": [[0, 1], [1, 2], [2, 3], [3, 4], [4, 5], [5, 6], [6, 7], [7, 8], [8, 9], [9, 10], [10, 11], [11, 0]], "Segments": [[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]]}	{"Points": [[12.5, 0.0], [12.5, 22.5], [12.5, 45.0], [0.0, 22.5], [25.0, 22.5]], "Lines": [[0, 1], [4, 1], [2, 1], [3, 1]], "Segments": [[0], [1], [2], [3]]}
T	[[0.0, 25.0], [25.0, 25.0], [25.0, 20.0], [15.0, 20.0], [15.0, 0.0], [10.0, 0.0], [10.0, 20.0], [0.0, 20.0]]	[[12.5, 0.0], [12.5, 22.5], [25.0, 22.5], [0.0, 22.5]]	{"Points": [[0.0, 25.0], [25.0, 25.0], [25.0, 20.0], [15.0, 20.0], [15.0, 0.0], [10.0, 0.0], [10.0, 20.0], [0.0, 20.0]], "Lines": [[0, 1], [1, 2], [2, 3], [3, 4], [4, 5], [5, 6], [6, 7], [7, 0]], "Segments": [[0, 1, 2, 3, 4, 5, 6, 7]]}	{"Points": [[12.5, 0.0], [12.5, 22.5], [25.0, 22.5], [0.0, 22.5]], "Lines": [[0, 1], [1, 2], [3, 1]], "Segments": [[0], [1], [2]]}
I_scaled_2	[[10.0, 10.0], [20.0, 10.0], [20.0, 40.0], [10.0, 40.0]]	[[15.0, 10.0], [15.0, 40.0]]	{"Points": [[10.0, 10.0], [20.0, 10.0], [20.0, 40.0], [10.0, 40.0]], "Lines": [[0, 1], [1, 2], [2, 3], [3, 0]], "Segments": [[0, 1, 2, 3]]}	{"Points": [[15.0, 10.0], [15.0, 40.0]], "Lines": [[0, 1]], "Segments": [[0]]}
L_scaled_2	[[10.0, 10.0], [20.0, 10.0], [20.0, 60.0], [70.0, 60.0], [70.0, 70.0], [10.0, 70.0]]	[[15.0, 10.0], [15.0, 65.0], [70.0, 65.0]]	{"Points": [[10.0, 10.0], [20.0, 10.0], [20.0, 60.0], [70.0, 60.0], [70.0, 70.0], [10.0, 70.0]], "Lines": [[0, 1], [1, 2], [2, 3], [3, 4], [4, 5], [5, 0]], "Segments": [[0, 1, 2, 3, 4, 5]]}	{"Points": [[15.0, 10.0], [15.0, 65.0], [70.0, 65.0]], "Lines": [[0, 1], [1, 2]], "Segments": [[0, 1]]}

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Data Explanation

Column information is as below:

- ShapeName (text): name of the shape. Just for visualization/reports.
- Profile (text): List of Points coordinates (x,y) representing outer profile shape, typically closed.
- Midcurve (text): List of Points coordinates (x,y) representing inner midcurve shape, typically open.
- Profile_brep (text): Dictionary in Brep format representing outer profile shape, typically closed.
- Midcurve_brep (text): Dictionary in Brep format representing inner midcurve shape, typically open.

Each Segment is a continuous list of lines. In case of, say 'Midcurve-T', as there is an intersection, we can treat each line in a separate segment. In the case of 'Profile O', there will be two segments, one for outer lines and another for inner lines. Each line is a list of points, for now, linear. Points is a list of coordinates (x,y), later can be (x,y,z).

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Data Resolution

- Once we have this Brep representations of both, profile and the corresponding midcurve, in the text form, then we can try various machine translation approaches or LLM based fine tuning or few-shots prompt engineering.
- One major advantage of text based method over image based method is that image output still has stray pixels, cleaning which will be a complex task. But the text method has exact points. It may just give odd lines, which can be removed easily.

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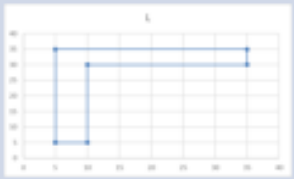
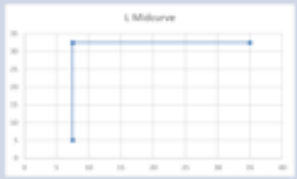
Prompt based techniques

Few Shots Prompt

```
You are a geometric transformation program that transforms input 2D polygonal
     profile to output 1D polyline profile. Input 2D polygonal profile is
     defined by set of connected lines with the format as: ...

Below are some example transformations, specified as pairs of 'input' and the
     corresponding 'output'. After learning from these examples, predict the
     'output' of the last 'input' specified.
Do not write code or explain the logic but just give the list of lines with
     point coordinates as specified for the 'output' format.

input:[((5.0,5.0), (10.0,5.0)), ... ((5.0,35.0), (5.0,5.0))]
output: [((7.5,5.0), (7.5, 32.5)), ... ((35.0, 32.5) (7.5, 32.5))]

input: [((5,5), (10, 5)), ...  (5, 20)), ((5, 20),(5,5))]
output: [((7.5, 5), (7.5, 20))]

:
input:[((0, 25.0), (25.0,25.0)),...  ((0,20.0),(0, 25.0))]
output:
```

Few Shot Examples Shapes

The first input example above represents 'L' shape (shown below) and the second is an 'I', whereas the 3rd is a 'Plus' sign shape.

Profile Data		Profile Picture	Midcurve Data		Midcurve Picture
5.0	5.0		7.5	5.0	
10.0	5.0		7.5	32.5	
10.0	30.0		35.0	32.5	
35.0	30.0		7.5	32.5	
35.0	35.0				
5.0	35.0				

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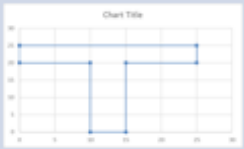
Few Shot Examples Shapes

The last shape for which LLM has been asked for the answer is actually a 'T' shape. The picture below shows the correct/actual answer as well.

Profile Data		Profile Picture	Midcurve Data		Midcurve Picture
0	25.0		12.5	0	
25.0	25.0		12.5	22.5	
25.0	20.0		25.0	22.5	
15.0	20.0		0	22.5	
15.0	0				
10.0	0				
10.0	20.0				
0	20.0				

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Output

And the outputs computed by various LLMs (ChatGPT, Perplexity AI, Bard) , along with the real/actual answer:

```
Actual: [((12.5,0), (12.5,22.5)), ((12.5,22.5),(25.0,22.5)),
     ((12.5,22.5),(0,22.5))]
ChatGPT: [((2.5, 0), (2.5, 22.5)), ((2.5, 22.5), (2.5, 45.0)), ((2.5, 22.5),
     (25.0, 22.5)), ((2.5, 22.5), (12.5, 22.5)), ((2.5, 22.5), (0, 22.5)),
     ((2.5, 22.5), (25.0, 22.5))]
Perplexity: [((12.5,0), (12.5, 22.5)), ((12.5, 22.5),(12.5,45.0)), ((12.5,
     22.5), (0,22.5)), ((12.5, 22.5), (25.0,22.5))]
Bard: [((12.5, 0), (12.5, 25.0)), ((12.5, 25.0), (25.0, 25.0)), ((25.0, 25.0),
     (25.0, 0))]
```

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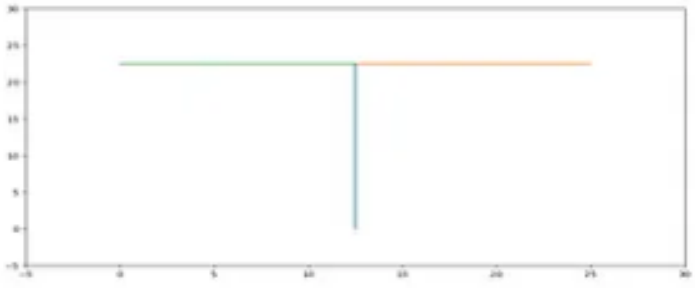
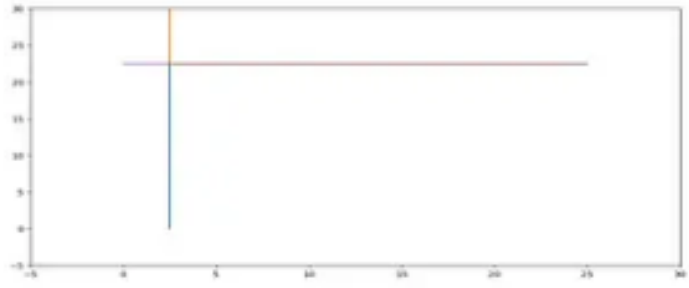
Output

Visually here is how results from different LLMs look:

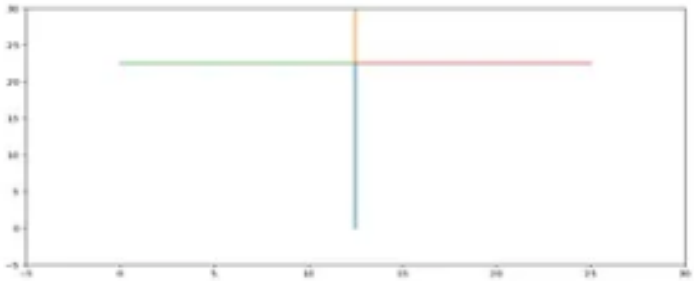
Actual/Expected



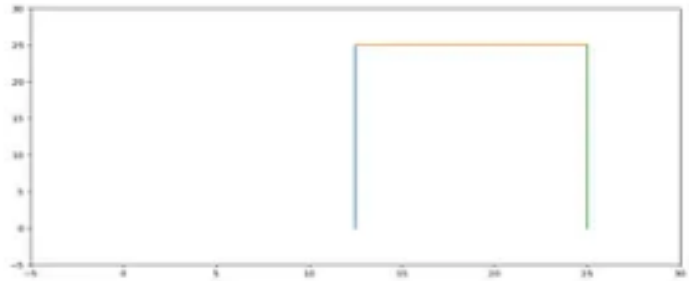
ChatGPT



Perplexity AI



Bard



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Interpretation

All of the above have failed. Even latest, the results are:

- `llama 7B g4_0 ggml: (8, 17) & (64, 32)`: Wrong.
- `Bard: [((8.33,5),(8.33, 22.5)), ((8.33, 22.5), (25,22.5)), ((8.33, 22.5), (0,25))]`: Wrong.
- `Hugging Chat: [((12.5, 0), (12.5, 22.5)), ((12.5, 22.5), (25.0, 22.5)), ((25.0, 22.5), (25.0, 25.0))]`: a bit wrong on the last line
- `GPT-4: [((12.5,0), (12.5,22.5)), ((12.5,22.5),(0,22.5)), ((12.5,22.5),(25.0,22.5))]` just change in sequence of lines, and that's inconsequential, so the answer is correct.

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Interpretation

LLMs by an large seem to have failed for such simple shapes.
There could be two prominent reasons:

- The prompt design was not effective and could be improved upon.
- The LLM model itself is not able to learn the pattern and predict well.

The current geometry representation as a sequence of lines, has limitations.
Trying to look for a good representation to store geometry/graph/network as text so that NLP (Natural Language Techniques) can be applied.

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Fine-tuning based techniques

Training Data

```
from datasets import load_dataset, Dataset, DatasetDict

base_url = "/content/drive/MyDrive/ImpDocs/Work/AICoach/Notebooks/data/"
dataset = load_dataset("csv", data_files={"train": base_url + "midcurve_llm_train.csv",
                                          "test": base_url + "midcurve_llm_test.csv",
                                          "validation": base_url + "midcurve_llm_val.csv"})
DatasetDict({
    train: Dataset({
        features: ['ShapeName', 'Profile', 'Midcurve', 'Profile_brep', 'Midcurve_brep'],
        num_rows: 793
    })
    test: Dataset({
        features: ['ShapeName', 'Profile', 'Midcurve', 'Profile_brep', 'Midcurve_brep'],
        num_rows: 99
    })
    validation: Dataset({
        features: ['ShapeName', 'Profile', 'Midcurve', 'Profile_brep', 'Midcurve_brep'],
        num_rows: 100
    })
})
```

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Data Preprocessing

The dataset is used to fine-tune the base model called "Salesforce/codet5-small". Trained model is saved and used for inference on test samples.

```
from transformers import T5ForConditionalGeneration, AdamW, get_linear_schedule_with_warmup
import pytorch_lightning as pl

class CodeT5(pl.LightningModule):
    def __init__(self, lr=5e-5, num_train_epochs=15, warmup_steps=1000):
        super().__init__()
        self.model_name = "Salesforce/codet5-small"
        self.model = T5ForConditionalGeneration.from_pretrained(self.model_name)
        self.save_hyperparameters()

    def forward(self, input_ids, attention_mask, labels=None):
        outputs = self.model(input_ids=input_ids, attention_mask=attention_mask, labels=labels)
        return outputs
        :
        :

model = CodeT5()

trainer = Trainer(max_epochs=5,accelerator="auto",# gpus=1,
                  default_root_dir="/content/drive/MyDrive/CodeT5/Notebooks/Checkpoints",
                  logger=wandb_logger,
                  callbacks=[early_stop_callback, lr_monitor])
trainer.fit(model)
```

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Inferencing

The output predicted far away from the corresponding ground truth.
There could be many reasons for the mismatch such as the quality of LLM, training parameters, and above all, need for a far bigger dataset for fine-tuning.
But overall, the approach and preliminary results look promising to warrant further investigations.

```
input_ids = tokenizer(test_example['Profile_brep'], return_tensors='pt').input_ids
outputs = model.generate(input_ids)

print("Ground truth:", test_example['Midcurve_brep'])
print("Generated Midcurve:", tokenizer.decode(outputs[0], skip_special_tokens=True))

Ground truth: "{\"Points\": [[−8.4, 3.28], [−20.68, −5.33]], \"Lines\": [[0, 1]], \"Segments\": [[0]]}"
Generated Midcurve: "{\"Points\": [[−8.83, 4.32], [−21.23
```

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Summary

- Various applications need lower dimensional representation of shapes.
- Midcurve is one- dimensional(1D) representation of a two-dimensional (2D) planar shape.
- Used in animation, shape matching, retrieval, finite element analysis, etc.

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Summary

- Approaches: Thinning, Medial Axis Transform (MAT), Chordal Axis Transform (CAT), Straight Skeletons, etc., all of which are rule-based.
- Proposing a novel method called MidcurveNN which uses Encoder-Decoder neural network for computing midcurve from images of 2D thin polygons in supervised learning manner.

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Summary

- This dimension reduction transformation from input 2D thin polygon image to output 1D midcurve image is learnt by the neural network,
- Which can then be used to compute midcurve of an unseen 2D thin polygonal shape.

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Summary

- Traditional methods of computing midcurves are predominantly rules-based and thus, have limitation of not developing a generic model which will accept any input shape.
- A novel Large Language Model based approach attempts to build such a generic model.
- One such model, GPT-4, seems to be very effective. Although other proprietary and open-source models need to catch-up with GPT-4, even GPT-4 needs to be developed further to understand not just sequential lines but graphs/networks with different shapes, essentially, the geometry.

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Summary

- This research significantly advances midcurve computation by exploring the interplay between established methodologies and cutting-edge approaches, particularly integrating Large Language Models (LLMs).
- Emphasizing the nuanced nature of geometric dimension reduction, it identifies challenges in handling variable-length input data, representing intricate shapes, and addressing limitations in existing models.

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MidcurveLLM Architecture

- Utilizes an Encoder-Decoder architecture and B-rep structures.
- Showcases promise, despite discrepancies with ground truths.

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Implications and Future Directions

- Points to the need for more extensive datasets and refined training parameters.
- Serves as a crucial catalyst for advancing midcurve computation methodologies.
- Invites further scrutiny and advancements in the transformative intersection of geometry and advanced machine learning.

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- Presentation: https://drive.google.com/file/d/1Tx5JJK1_LUfIMTW-B43HNN2GDMKJMOxR/preview
- Short paper: https://vixra.org/abs/1904.0429
- Github repo, source code: https://github.com/yogeshhk/MidcurveNN

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Thanks . . .

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