A Fine Matrix

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BROWN

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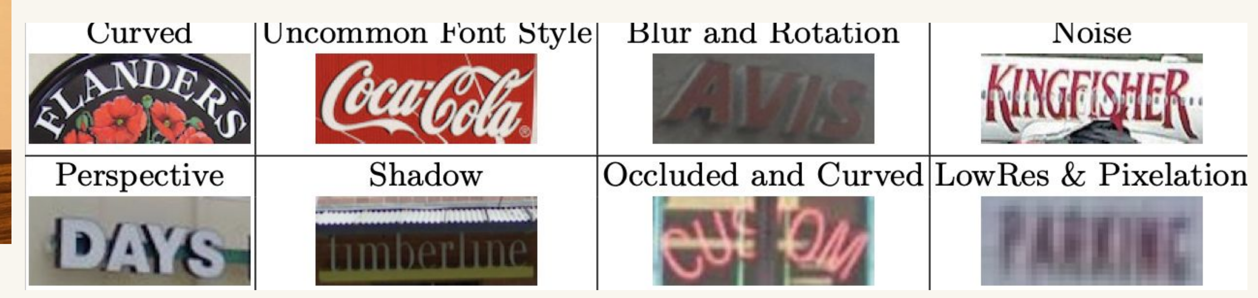
Goals and Motivations

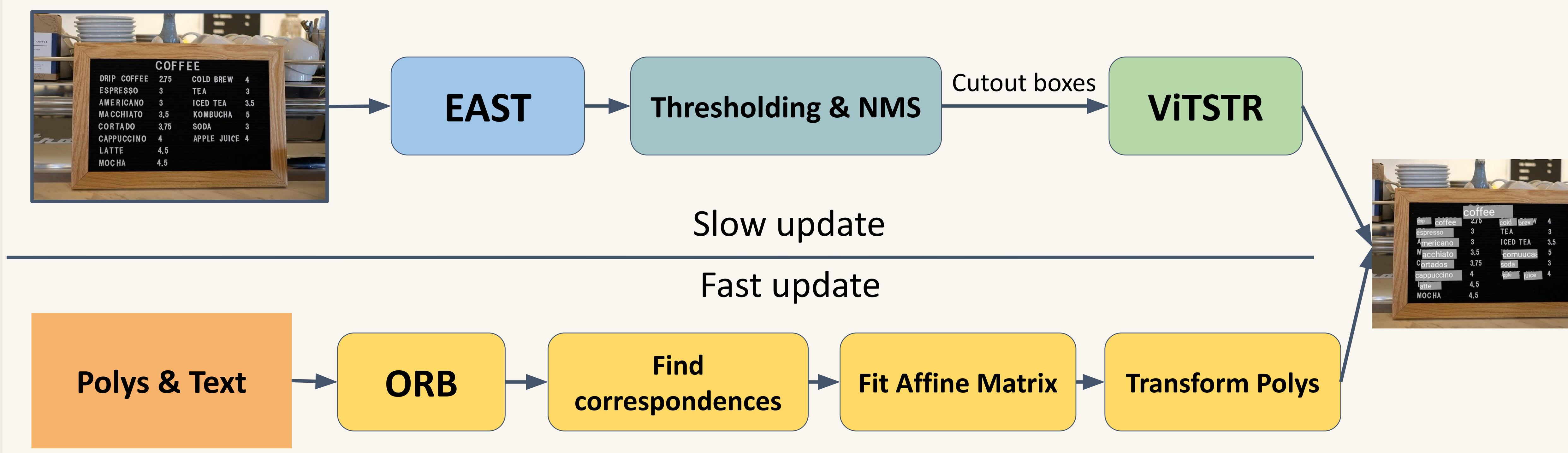
Our goal is to design a model that detects and translates text within different images, similar to a scoped-down version of the Google Lens Translate feature.

Importance: In an increasingly globalized world, there is a rising demand for the ability to comprehend and translate text across languages.

Challenge: in natural scenes, text lines may appear in a range of languages, styles, orientations, and other variations.



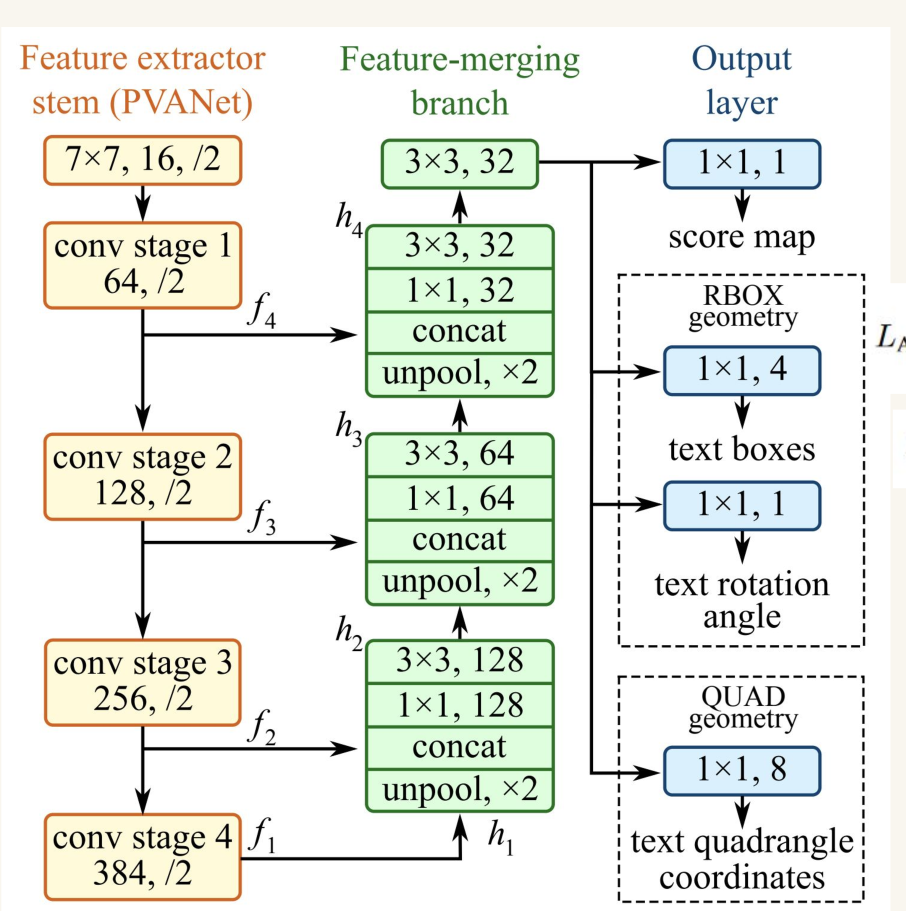
Architecture



EAST Detector

We implemented an EAST detector for text detection. The model makes use of a **fully convolutional network** (FCN) with **feature-merging at different scales** to produce text predictions (as rotated rectangles), which are then processed using thresholding and **Non-Maximum Suppression** to cull the poor candidates

Model Architecture:



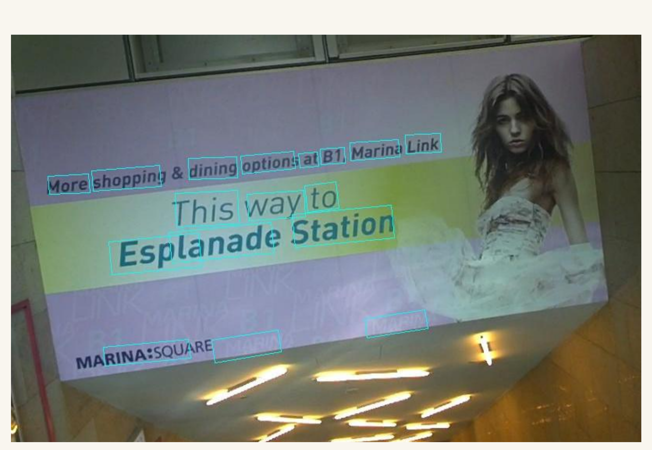
$$L = L_s + \lambda_g L_g$$

$$Dice = \frac{2\,|A \cap B|}{|A| + |B|}$$

$$L_{\mathrm{AABB}} = -\log \mathrm{IoU}(\hat{\mathbf{R}}, \mathbf{R}^*) = -\log \frac{|\hat{\mathbf{R}} \cap \mathbf{R}^*|}{|\hat{\mathbf{R}} \cup \mathbf{R}^*|}$$

$$L_\theta(\hat{\theta}, \theta^*) = 1 - \cos(\hat{\theta} - \theta^*).$$

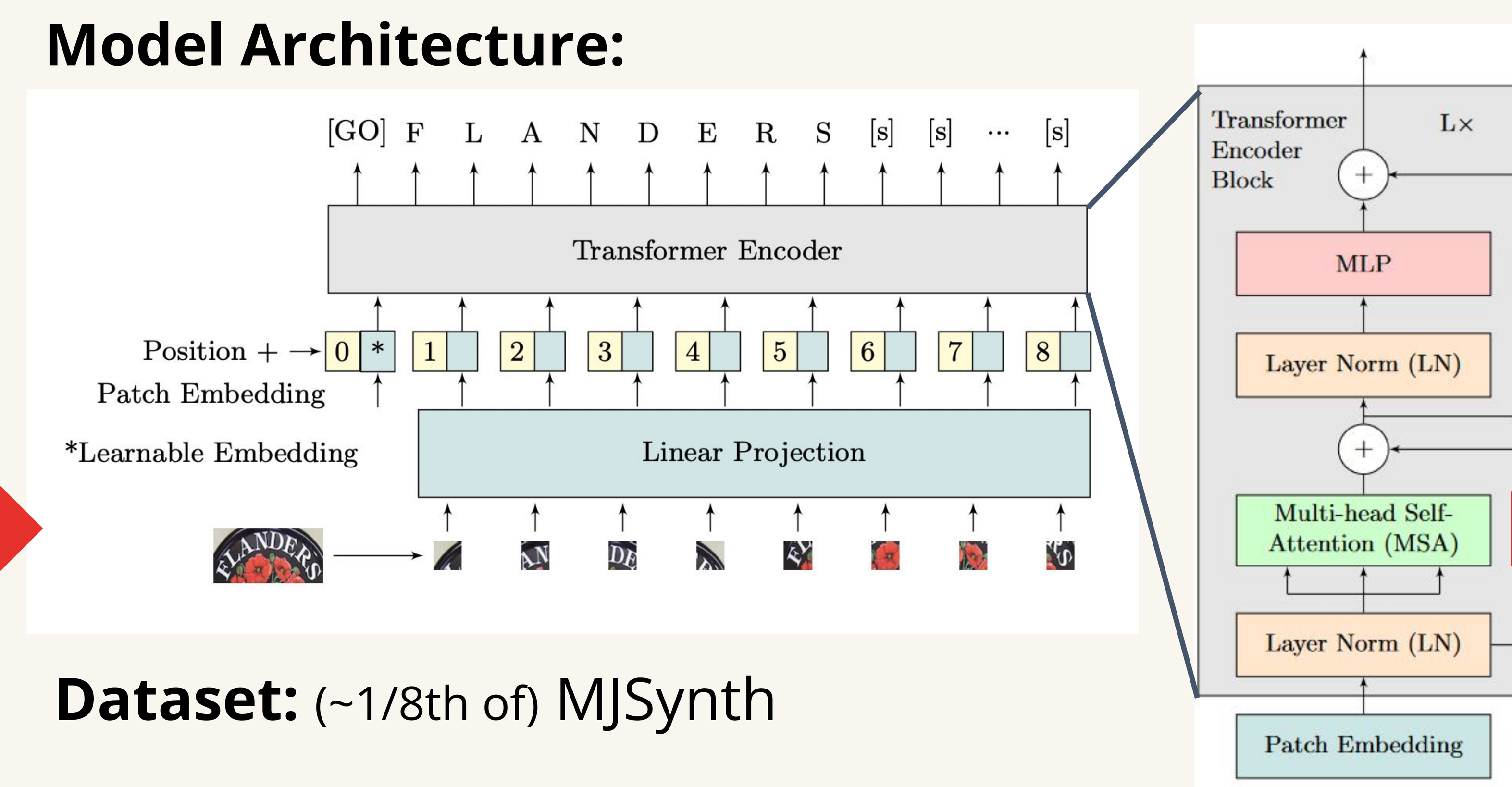
Dataset: ICDAR 2015



ViTSTR

For text recognition, we made use of a ViTSTR model, which uses the model weights of **Data efficient image Transformer**, which was trained used **hard-label distillation** with a strong **convnet teacher.**

Model Architecture:

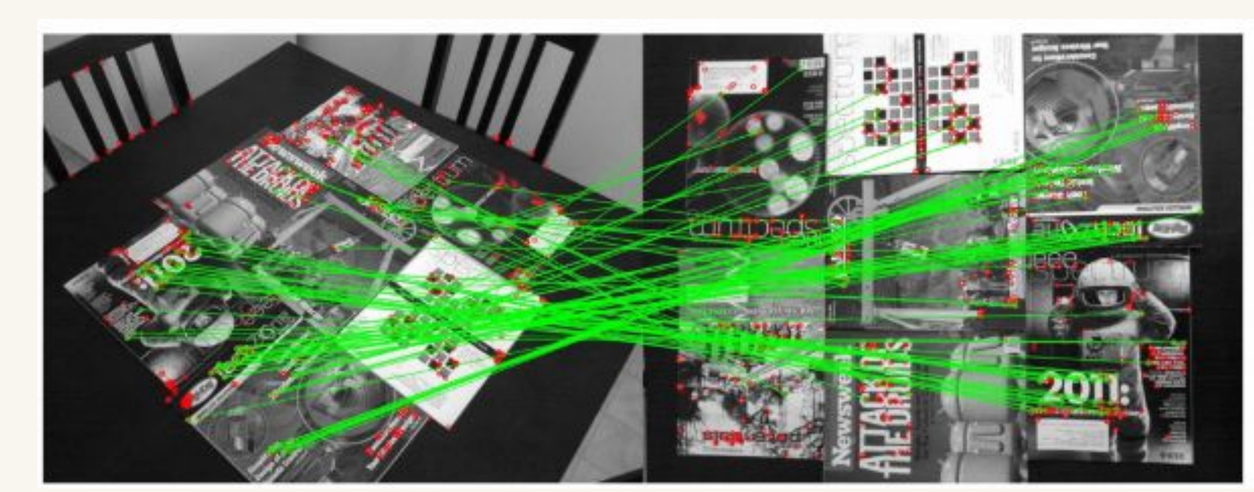


Dataset: (~1/8th of) MJSynth

Rendering & ORB

Once we have the polygons and text, we use the **Google Translate API** to receive translations in the target language. Then we render boxes and the translation on the source image, matching the scale and orientation.

As the goal is to have a live video, we need a faster way to update the polygons than a full forward pass of the neural network. We generate **ORB feature descriptors** (ORB utilizes the FAST algorithm to find a range of keypoints and BRIEF descriptors modified to account for rotation) and **find correspondences** to **fit an affine matrix** that describes the transformation between the slow update frame (t=0) and later frames (t=1,2,3,...). We apply this affine matrix to the polygons from t=0 to determine their likely location at the current time frame.



References

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