# **Boosting Semi-Supervised Scene Text Recognition**From Viewing to Understanding

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# What is STR?

#### Introduction

- Scene Text Recognition (STR) is the task of converting text images found in natural environments into machine-readable characters.
- STR enables computers to "read" text in photos, signs, menus, and documents - making our visual world accessible to machines.

## Background

- Critical applications include: Assistance for visually impaired,
   Document digitization, Visual search and information retrieval
- STR pipeline include: Text detection, Character
- recognition, and Contextual correction.



# Challenges of STR

- "Limited labeled data for diverse text styles"
- Annotation is expensive and time-consuming
- Most models rely on synthetic datasets

# "Real-world text varies greatly in appearance"

- Enormous variation in fonts, colors and backgrounds
- Environmental factors create additional complexity

#### "Difficulty recognizing artistic and oriented text"

- Decorative fonts break conventional character structure
- Poor performance on WordArt and Union14M-Benchmark

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# Methodology

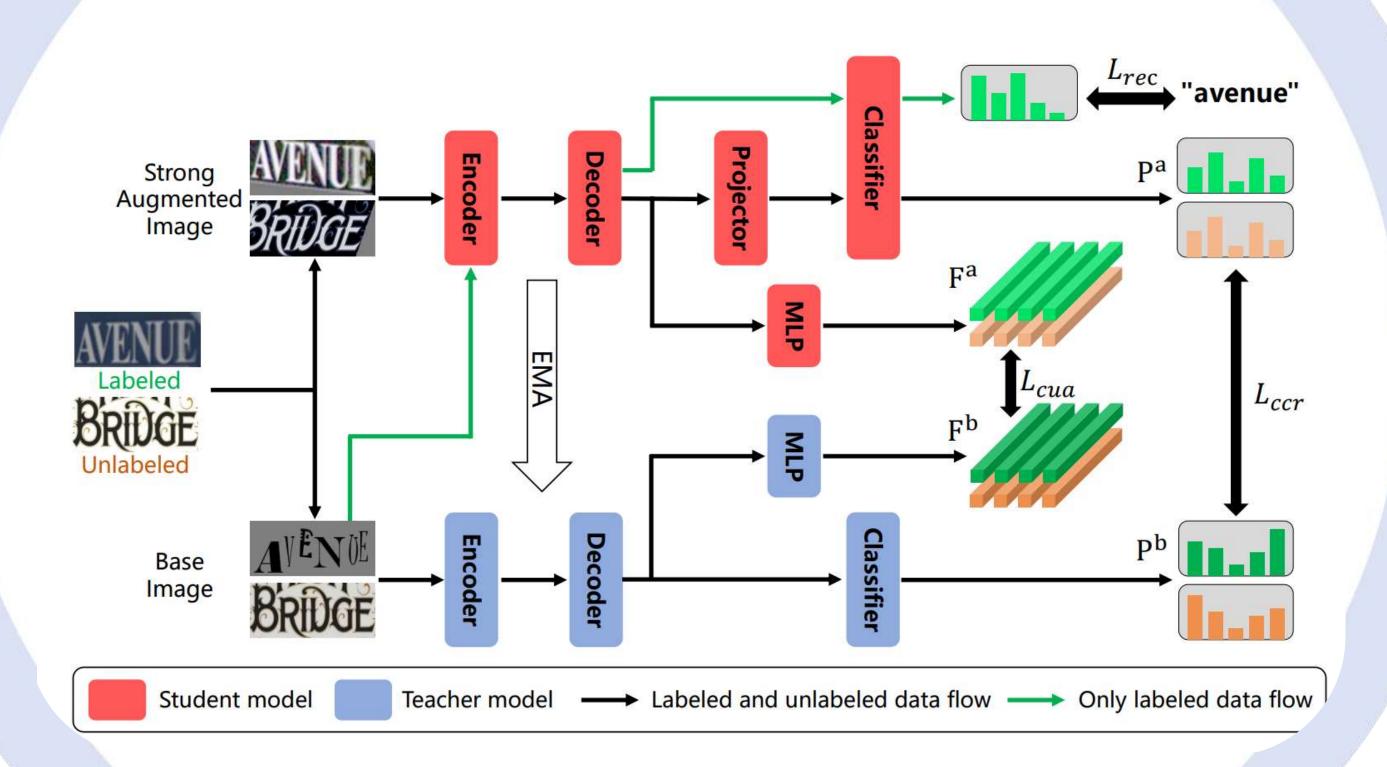
# Semi-supervised Learning Framework

- •Teacher-Student architecture for knowledge transfer
- Leverages both labeled synthetic and unlabeled real data
- •Mean Teacher with Exponential Moving Average (EMA) updates
- •Strong and weak augmentation paths for consistency learning

## **Training Strategy**

- •Supervised learning with labeled synthetic data
- •Consistency regularization with unlabeled real-world data
- Progressive feature alignment during training
- Joint optimization of recognition and feature space

# Framework Overview



# Innovation

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## Online Generation Strategy (OGS)

- Generates diverse character styles during training without backgrounds
- Creates unified representation forms for characters across domains
- Bridges the gap between synthetic and real-world text appearance
- Enhances model generalization to unseen text styles

# Character Unidirectional Alignment Loss (CUA)

- Novel loss function that prevents feature collapse in semi-supervised learning
- Maintains distinctive features between different characters
- Unidirectional constraint allows feature refinement without oversmoothing
- Significantly improves clustering of samecharacter variants

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# Results

# ParSeq ViSu

# **Feature Visualization**

- ViSu shows improved character clustering with clear boundaries
- Better separation between similar characters
- More coherent grouping within same character class
- Enhanced feature organization boosts recognition accuracy

## **Ablation Analysis**

- •(b): Without CUA Loss poorer clustering
  •(c): Full model
- •(c): Full model optimized feature space
- •OGS contribution:
- +8.2% accuracy gain
  •CUA Loss: +10.2%
  character discrimination
  improvement

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## **Performance Highlights**

- •State-of-the-art on artistic text: +25.1% on WordArt, +30.8% on ArT
- •Strong on regular benchmarks: IIIT (+1.7%), SVT (+2.4%)
- •60.3% average accuracy across all datasets (table, bottom right)

# Conclusions

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# **Key Findings**

- •Semi-supervised learning successfully bridges synthetic-to-real gap
- Character-level feature alignment is critical for STR robustness
- •View-and-Summarize approach handles diverse text styles effectively

## **Main Contributions**

- Novel semi-supervised framework for STR with minimal labeled data
- Online Generation Strategy (OGS) for diverse character synthesis
- •Character Unidirectional Alignment Loss for feature space optimization
- •State-of-the-art performance on challenging artistic and oriented text

# **Future Directions**

- •Extending to end-to-end text spotting in complex scenes
- •Exploring language-aware feature alignment for better contextual understanding
- •Adapting framework for low-resource languages and specialized domains

Method	Datasets	Cur	M-O	Art	Con	Sal	M-W	Gen	AVG
ParSeq [2]	10% (MJ + ST) + OGS	54.3	15.7	52.3	53.2	67.3	55.9	58.8	51.1
MGP [41]	10% (MJ + ST) + OGS	46.8	10.5	49.9	33.0	55.1	26.7	55.8	39.7
CLIPOCR [43]	10% (MJ + ST) + OGS	57.1	13.0	57.1	49.2	65.5	60.2	59.8	51.7
LPV [52]	10% (MJ + ST) + OGS	58.6	12.9	53.3	53.3	67.4	59.3	56.9	51.7
LISTER [5]	10% (MJ + ST) + OGS	52.0	13.7	48.9	54.4	59.8	54.5	61.0	49.2
TRBA-cr [54]	10% (MJ + ST) + OGS	67.1	17.4	58.6	51.1	67.7	33.5	57.4	50.4
ViSu	10% (MJ + ST)	57.5	79.6	49.8	44.4	66.8	50.4	59.2	58.2
ViSu	OGS	1.7	25.1	5.8	4.9	3.0	6.9	10.2	8.2
ViSu	10% (MJ + ST) + OGS	60.8	80.8	52.4	47.1	69.1	51.8	59.9	60.3



Source code