Latent Programmer:
Discrete Latent Codes for Program Synthesis

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Program Synthesis

Goal: Automatically generate programs given some specification that humans can easily provide, i.e. input-output (IO) examples or natural language descriptions

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Example 1: IO → String Transformation

1. "Mason Smith" → "Smith M"
2. "Henry Myers" → "Myers H"
3. "Barry Underwood" → "Underwood B"
4. "sandy Jones" → "Jones S"

GetToken_PROP_CASE_2 | " " | ToCase_UPPER(GetToken_CHAR_1)

Program Synthesis

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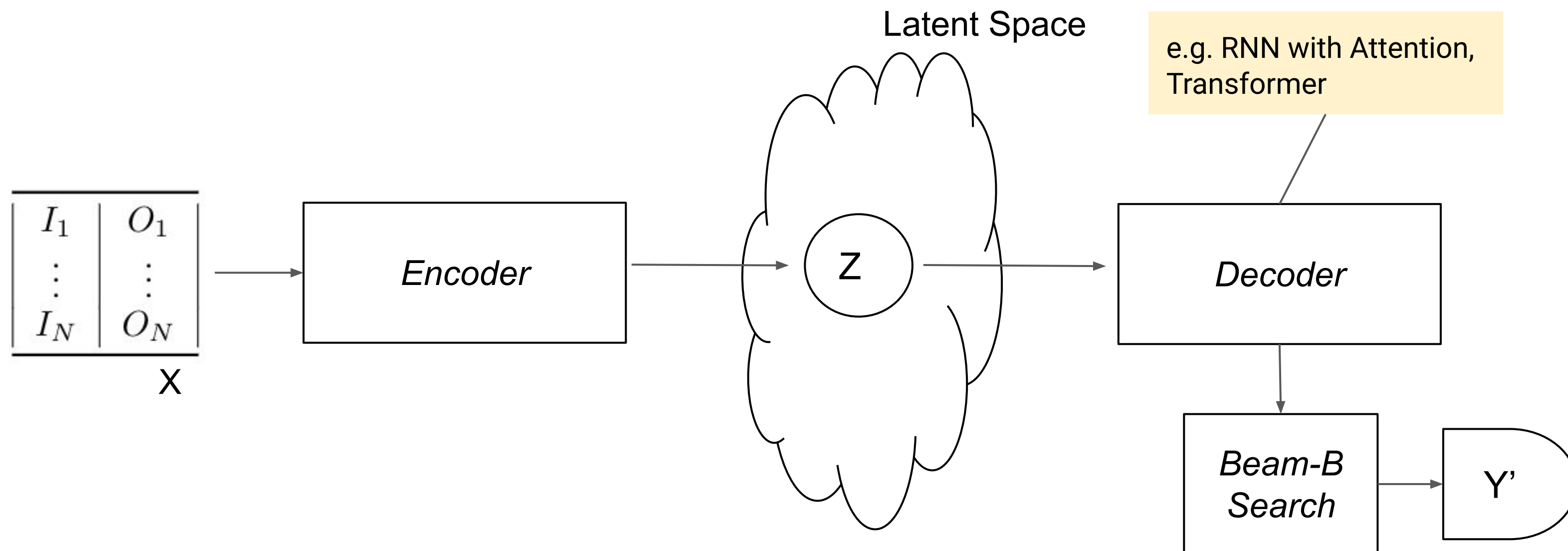
Example 2: Natural Language → Python Function

“return a list of words in the string s”

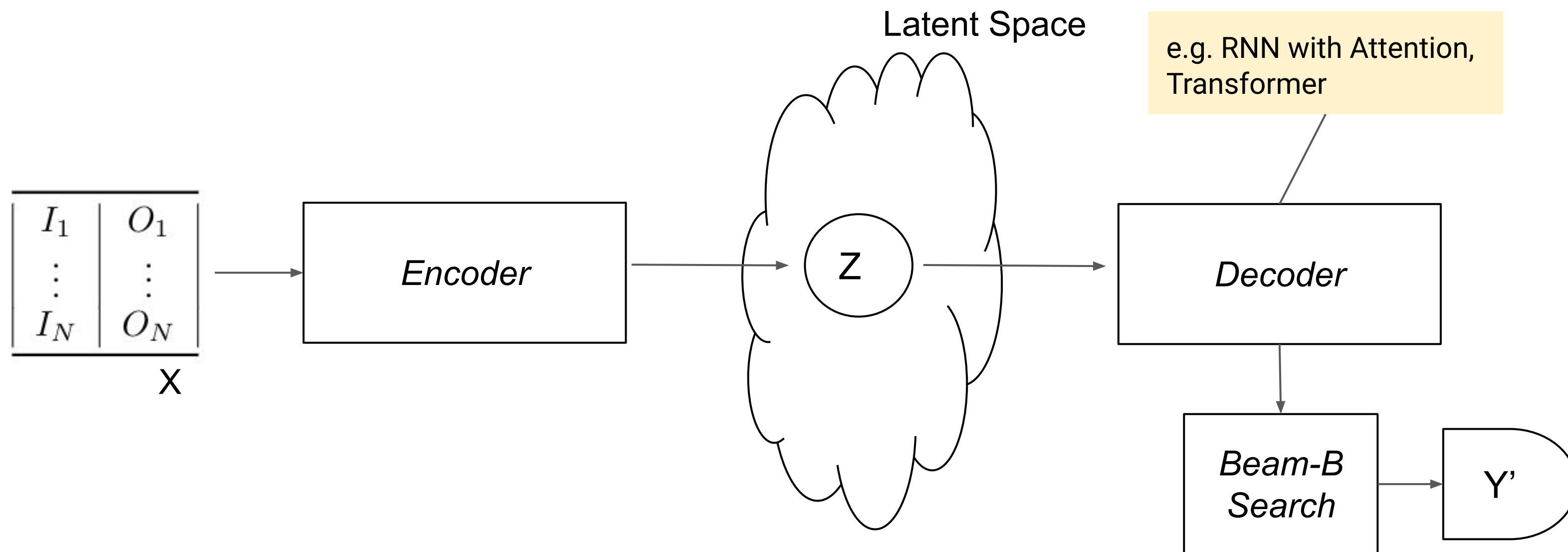
```
def split(s, sep=None, maxsplit=-1):
  return s.split(sep, maxsplit)
```

Neural Program Synthesis



Devlin et al., 2017

Neural Program Synthesis



Problem: Seq-to-seq networks do very well on simple tasks, but fail to infer more complicated programs.

Devlin et al., 2017

Two-Level Search: Motivation

Example problem: Find string transformation that maps inputs to outputs

1. “Jacob,Ethan,James 11” → “11:J.E.J.”
2. “Elijah,Daniel,Aiden 3162” → “3162:E.D.A”
3. “Rick,Oliver,Mia 26” → “26:R.O.M.”
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How might a person solve this problem?

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Intuition: People would first construct a high-level plan for the program, then fills in details of the program based on the plan.

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Number | 1st Initial | 2nd Initial | 3rd initial (High-level plan)

GetToken_NUMBER_1 | “:” | GetToken_ALL_CAPS_1 | “.” | GetToken_ALL_CAPS_2 | “.” | GetToken_ALL_CAPS_3 (Low-level program)

Two-Level Search: Plans

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Example 1:

Last Initial | First Name → GetToken | GetToken (Program Sketch)

Murali et al., 2018

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Example 2:

Last Initial | First Name →
GetToken_<HOLE>_<HOLE> | GetToken_WORD_<HOLE> (Program Sketch)

Nye et al., 2019

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Example 3 (this work):

Last Initial | First Name ⟶ TOK_2 | TOK_8 (Latent Code)

Latent Codes

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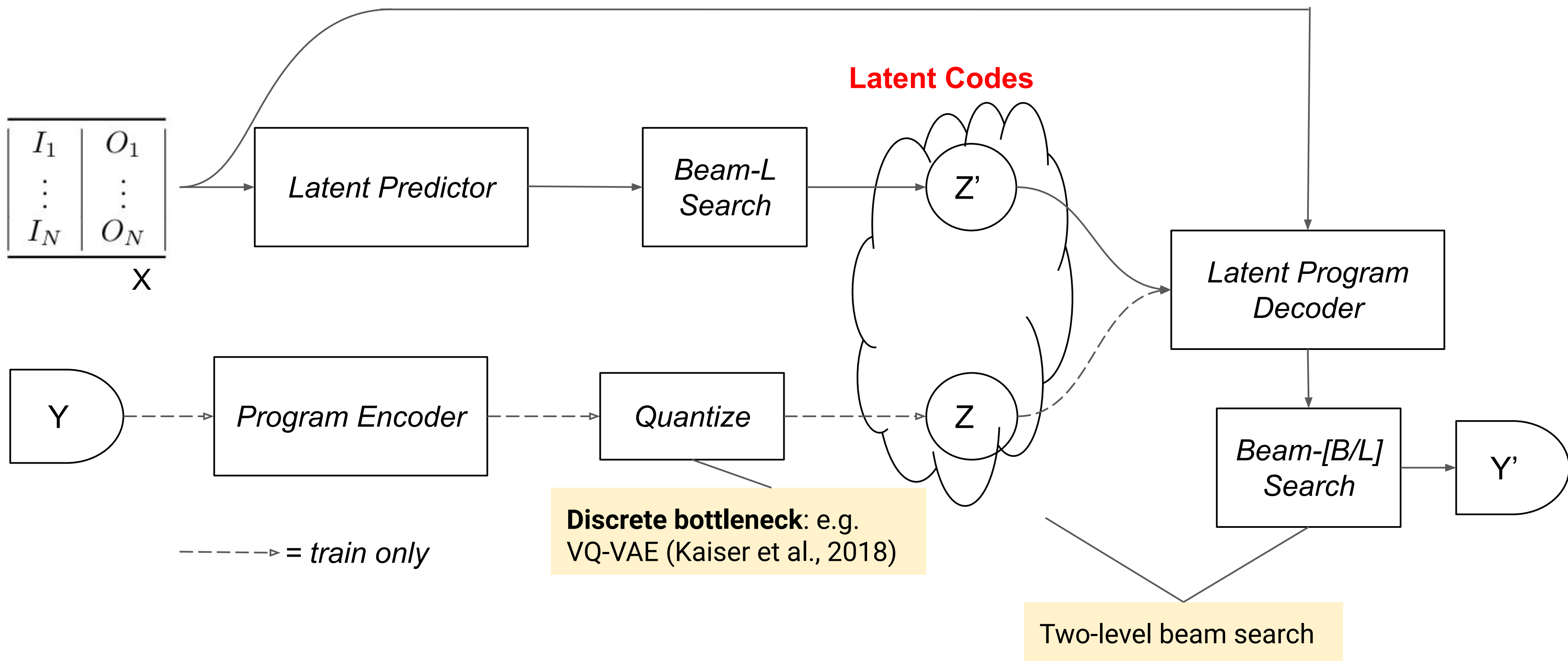
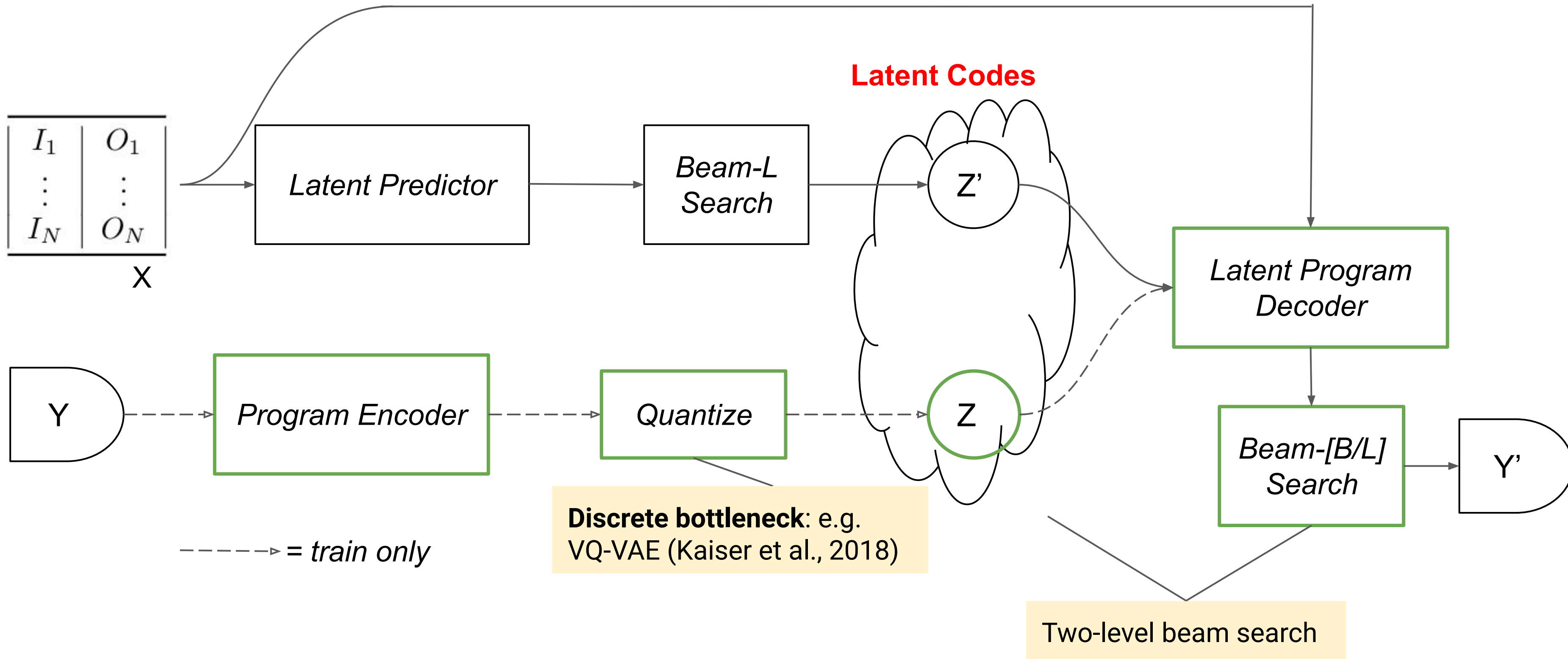
- Latent codes provide generality and flexibility. The model can assign arbitrary meanings to tokens in the latent space.
- How is it learned? Using a supervised technique where a discrete autoencoder generates intermediate latent code targets for the end-to-end prediction task. We consider using a VQ-VAE as the autoencoder (similarly done in Kaiser et al., 2018).

Latent Programmer



Training Loss 1: Fit Y’ to Y using Z (autoencoder loss)

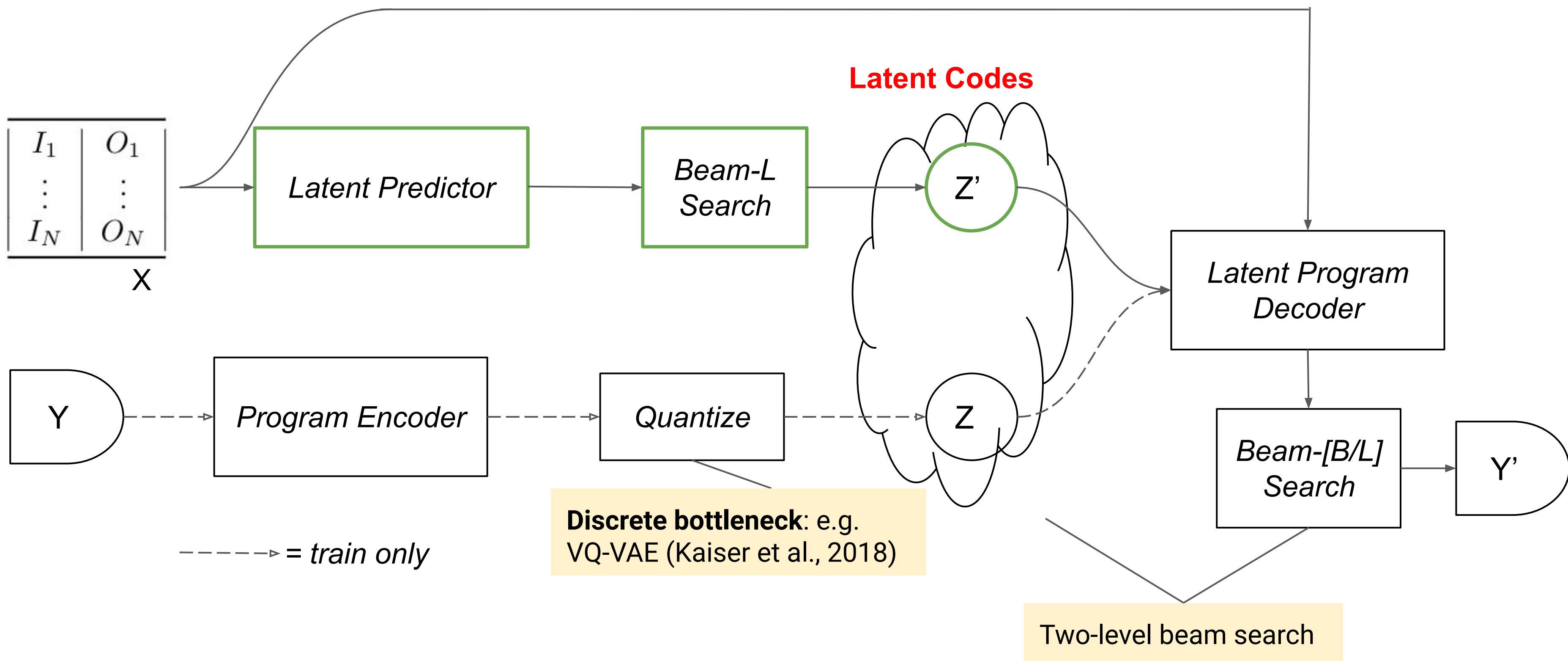
Latent Programmer



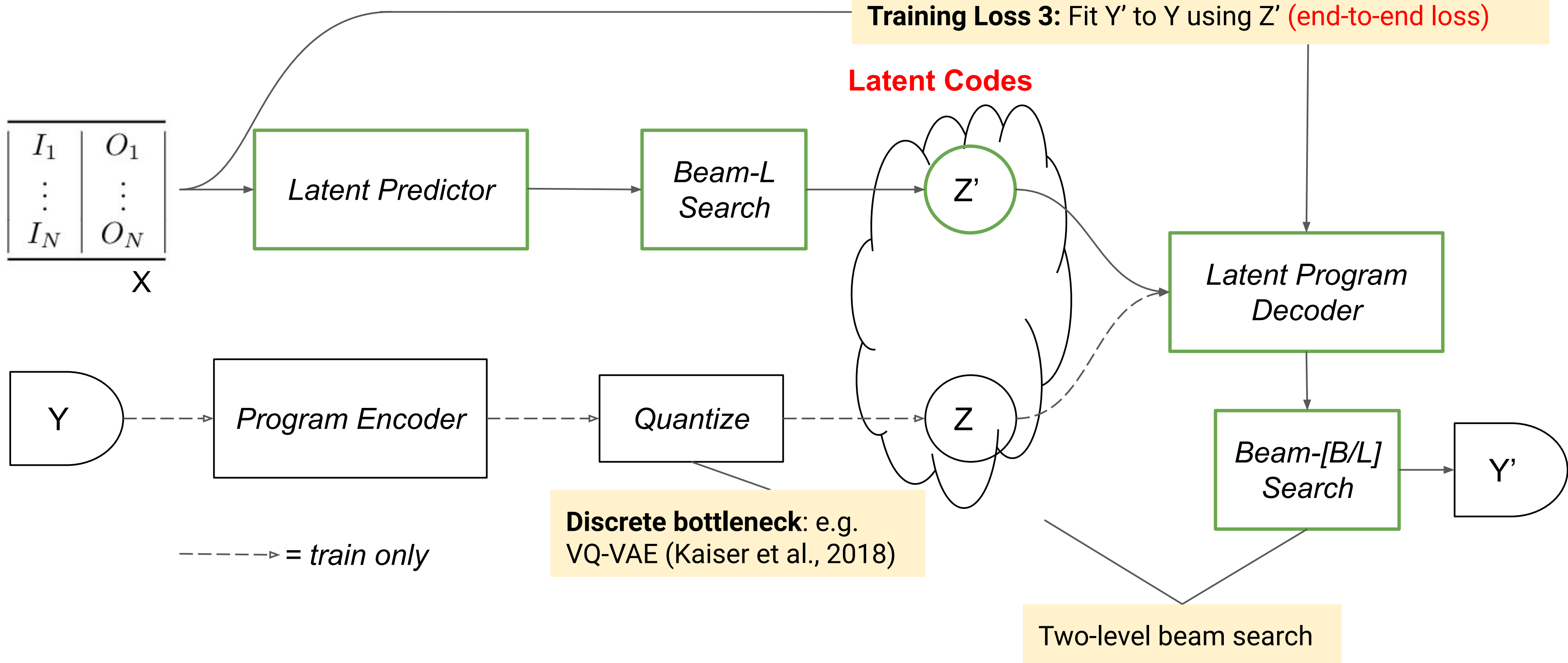
Latent Programmer

Training Loss 1: Fit Y' to Y using Z (autoencoder loss)

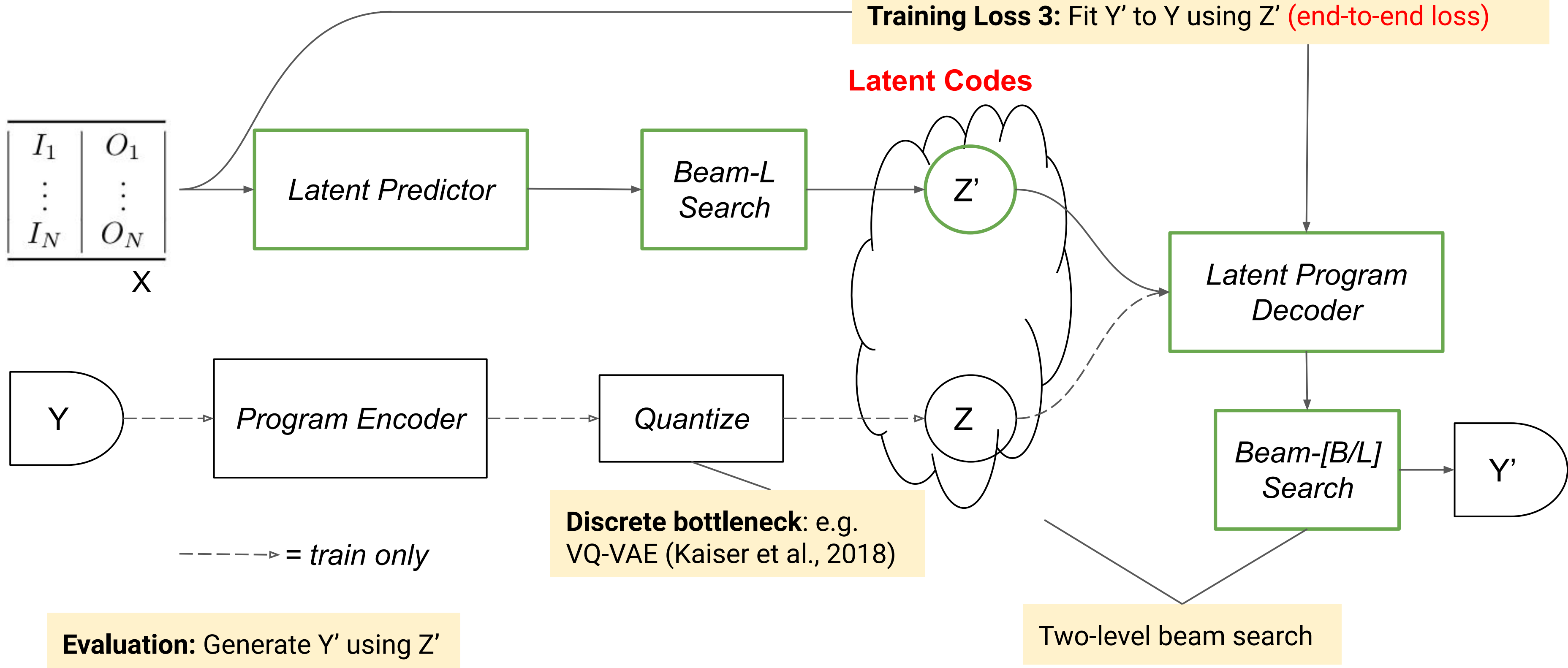
Training Loss 2: Fit Z' to Z (latent prediction loss)



Latent Programmer



Latent Programmer



String Transformation: Setup

String transformation DSL:

$$
\begin{array}{rcl}
\text{Program } Y & := & \texttt{Concat}(e_1, e_2, \ldots) \\
\text{Expression } e & := & f \mid n \mid n_1(n_2) \mid n(f) \mid \texttt{ConstStr}(c) \\
\text{Substring } f & := & \texttt{SubStr}(k_1, k_2) \mid \texttt{GetSpan}(r_1, i_1, b_1, r_2, i_2, b_2) \\
\text{Nesting } n & := & \texttt{GetToken}(t, i) \mid \texttt{ToCase}(s) \mid \texttt{Replace}(\delta_1, \delta_2) \mid \texttt{Trim}() \mid \texttt{GetUpto}(r) \mid \texttt{GetFrom}(r) \\
 & & \mid \texttt{GetFirst}(t, i) \mid \texttt{GetAll}(t) \\
\text{Regex } r & := & t_1 \mid \ldots \mid t_n \mid \delta_1 \mid \ldots \mid \delta_m \\
\text{Type } t & := & \texttt{NUMBER} \mid \texttt{WORD} \mid \texttt{ALPHANUM} \mid \texttt{ALL_CAPS} \mid \texttt{PROP_CASE} \mid \texttt{LOWER} \mid \texttt{DIGIT} \mid \texttt{CHAR} \\
\text{Case } s & := & \texttt{PROPER} \mid \texttt{ALL_CAPS} \mid \texttt{LOWER} \\
\text{Position } k & := & -100 \mid -99 \mid \ldots \mid 1 \mid 2 \mid \ldots \mid 100 \\
\text{Index } i & := & -5 \mid -4 \mid \ldots \mid -1 \mid 1 \mid 2 \mid \ldots \mid 5 \\
\text{Boundary } b & := & \texttt{START} \mid \texttt{END} \\
\text{Delimiter } \delta & := & \&,.?@()[]\%\{\}/ :;\$\#"' \\
\text{Character } c & := & A - Z \mid a - z \mid 0 - 9 \mid \&,.?@\ldots
\end{array}
$$

String Transformation: Setup

Dataset:

- Randomly sampled 2M programs from the DSL of 1-10 expressions
- Each program has 4 randomly generated IO examples: used heuristics to ensure each input mapped to non-empty output

Example problem:

Inputs	Outputs	Program
"Jacob,Ethan,James 11"	"11:J.E.J."	GetToken_NUMBER_1 | Const(:) |
"Elijah,Daniel,Aiden 3162"	"3162:E.D.A"	GetToken_ALL_CAPS_1 | Const(.) |
"Rick,Oliver,Mia 26"	"26:R.O.M."	GetToken_ALL_CAPS_2 | Const(.) |
"Mark,Ben,Sam 510"	"510:M.B.S."	GetToken_ALL_CAPS_3 | Const(.)

String Transformation: Results

Latent Programmer outperforms strong state-of-the-art-baselines

Results from ablation study:

- LSTM vs transformer
- Continuous autoencoder vs. discrete

Method	Accuracy		
	B = 1	10	100
RobustFill [LSTM]	45%	49%	61%
RobustFill [Transformer]	47%	51%	61%
Latent RobustFill [AE]	47%	50%	60%
Latent RobustFill [VAE]	46%	51%	62%
Latent Programmer	**51%**	**57%**	**68%**

Devlin et al., 2017

Comparison to other prior work:

Method	Accuracy
DeepCoder (Balog et al., 2017)	40%
SketchAdapt (Nye et al., 2019)	62%
Latent Programmer	**67%**

Another form of two-level search

String Transformation: Results

Example with long repetitive structure where baseline fails but Latent Programmer recovers the correct program

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"Jacob,Ethan,James 11"	"11:J.E.J."	GetToken_NUMBER_1 | Const(:) |
"Elijah,Daniel,Aiden 3162"	"3162:E.D.A"	GetToken_ALL_CAPS_1 | Const(.) |
"Rick,Oliver,Mia 26"	"26:R.O.M."	GetToken_ALL_CAPS_2 | Const(.) |
"Mark,Ben,Sam 510"	"510:M.B.S."	GetToken_ALL_CAPS_3 | Const(.)

RobustFill	GetAll_NUMBER | Const(:)| GetToken_ALL_CAPS_2 | Const(.)
LP	GetAll_NUMBER | Const(:) | GetToken_ALL_CAPS_1 | Const(.) | GetToken_ALL_CAPS_2 | Const(.) | GetToken_ALL_CAPS_-1 | Const(.)
LP Latent	TOK_14 | TOK_36 | TOK_36 | TOK_36

String Transformation: Analysis

Exploration-exploitation trade-off:
Higher latent beam size leads to more diverse programs

Latent Beam Size	Accuracy	Distinct n-Grams			
		n = 1	2	3	4
L = 1	50%	0.13	0.23	0.26	0.28
2	51%	0.13	0.24	0.26	0.28
3	**55%**	0.14	0.25	0.28	0.31
5	54%	0.14	0.26	0.29	0.32
10	54%	**0.14**	**0.26**	**0.30**	**0.33**

String Transformation: Analysis

Performs much better on longer (more complex) programs.

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Length	RobustFill Acc.	LP Acc.
1	**94.5%**	94.0%
2	83.9%	**84.6%**
3	**72.8%**	72.2%
4	63.1%	**66.1%**
5	47.1%	**49.8%**
6	40.6%	**43.0%**
7	30.2%	**34.6%**
8	22.7%	**28.4%**
9	18.6%	**27.0%**
10	14.4%	**25.6%**

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7	30.2%	**34.6%**
8	22.7%	**28.4%**
9	18.6%	**27.0%**
10	14.4%	**25.6%**

Tokens often have high-level semantic meaning

	TOK_3	TOK_4	TOK_5	TOK_6	TOK_7	TOK_8	TOK_9
Get First Number	12%	5%	0%	9%	70%	6%	0%
Get Last Number	22%	49%	0%	11%	8%	8%	0%
Get First Word	10%	20%	0%	56%	7%	9%	0%
Get Last Word	75%	4%	0%	6%	9%	6%	0%
Get First Alphanum	11%	3%	0%	35%	42%	9%	0%
Get Last Alphanum	45%	29%	0%	22%	0%	4%	0%

Python Code: Results

Latent Programmer also performs well in generating Python code from docstrings:

Docstring	Program
get an environment variable	`def set_key(key, val, key_prefix=None):` `  return return environ.get(key, key_prefix)`
return a list of the words in the string s	`def split(s, sep=None, maxsplit=-1):` `  return s.split(sep, maxsplit)`
mean squared error function	`def mean_squared_error(y_true, y_pred):` `  return tf.reduce_mean(tf.square((y_true - y_pred)))`

read a python file	`def read_file(fname):`
	`  f = open(fname)`
	`  with open(fname, 'r') as f:`
	`    f.seek(0)`
	`    return f.read()`

Method	BLEU		
	B = 1	10	100
Base (Wei et al., 2019)	10.4	-	-
Dual (Wei et al., 2019)	12.1	-	-
RobustFill [LSTM]	11.4	14.8	16.0
RobustFill [Transformer]	12.1	15.5	17.2
Latent Programmer	**14.0**	**18.6**	**21.3**

Wei et al., 2019

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Top program tokens (TF-IDF score) for select latent tokens.

0	_files	dirname	glob	isdir	makedir
1	server	_port	_socket	_password	host
2	pip	package	wheel	install	sudo
3	dt	interval	seconds	time	timestamp
4	timeout	_timeout	handle	future	notifier

Conclusion

Propose general two-level search where a high-level plan is generated, then program conditioned on the plan

Latent Programmer:

- Plans are latent codes, or sequences of discrete latent variables
- Latent space is learned in a supervised algorithm using a discrete autoencoder
- Two-level beam search on latent codes, then on program

Thank You!