Module 4.0 - Networks

Fusion

- Optimization across operator boundary
- Save speed or memory in by avoiding extra forward/backward
- Can open even great optimization gains

Simple Matmul Pseudocode

```
for outer_index in out.indices():
  for inner_val in range(J):
       out[outer_index] += A[outer_index[0], inner_val] * \
                           B[inner_val, outer_index[1]]
```

Compare to zip / reduce

Code

```
ZIP STEP
  C = zeros(broadcast_shape(A.view(I, J, 1), B.view(1, J, K)))
  for C_outer in C.indices():
      C[C_out] = A[outer_index[0], inner_val] * \
                 B[inner_val, outer_index[1]]
  REDUCE STEP
  for outer_index in out.indices():
     for inner_val in range(J):
        out[outer_index] = C[outer_index[0], inner_val,
                             outer_index[1]]
```

Diagram

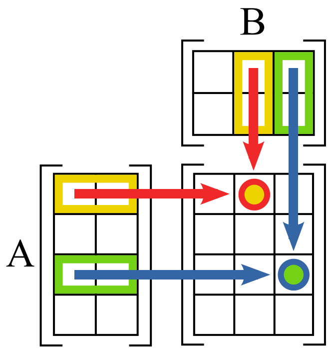
Large Square

Basic CUDA - Square Large

Basic CUDA ::

```
def mm_shared1(out, a, b, K):
    ...
    for s in range(0, K, TPB):
        sharedA[local_i, local_j] = a[i, s + local_j]
        sharedB[local_i, local_j] = b[s + local_i, j]
        ...
        for k in range(TPB):
            t += sharedA[local_i, k] * sharedB[k, local_j]
    out[i, j] = t
```

Non-Square - Dependencies



Challenges

- How do you handle the different size of the matrix?
- How does this interact with the block size?

Quiz

Quiz

Today's Class

- Architecture
- Memory
- Communication

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Goal: AI Tasks

- Sentiment Analysis
- Image Recognition

Natural Language Processing

- Systems for human language
- Broad area of study with lots of challenges
- Heavily uses ML, more in recent years

Sentiment Classification

- Canonical sentence classification problem
- Given sentence predict sentiment class
- Key aspects: word polarity

Data

This isn't a new idea

You'll probably love it

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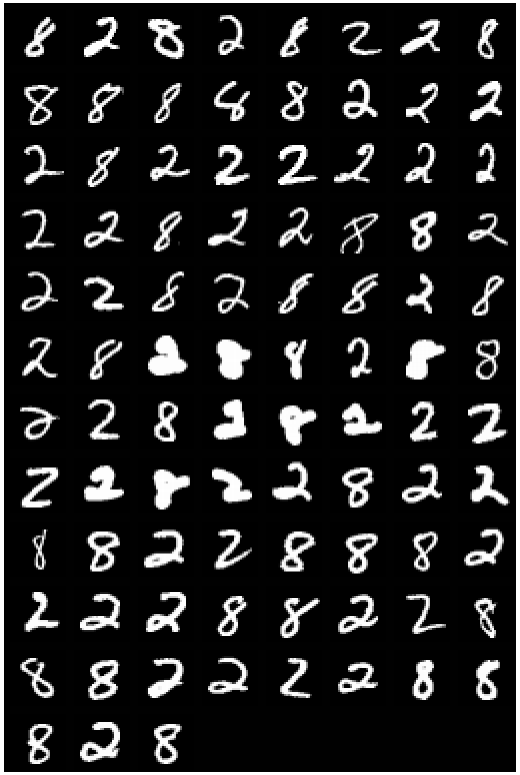
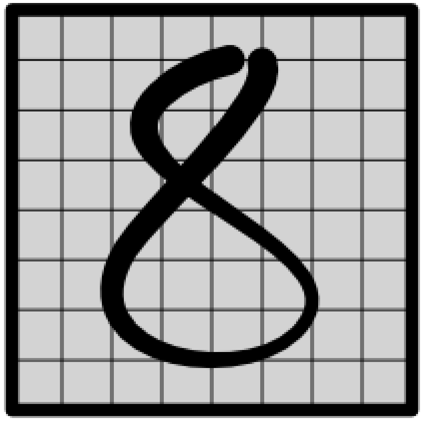
Image Recognition

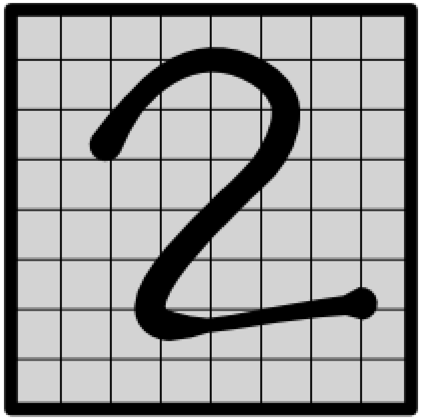
- Classical problem in intro machine learning.

Data Set

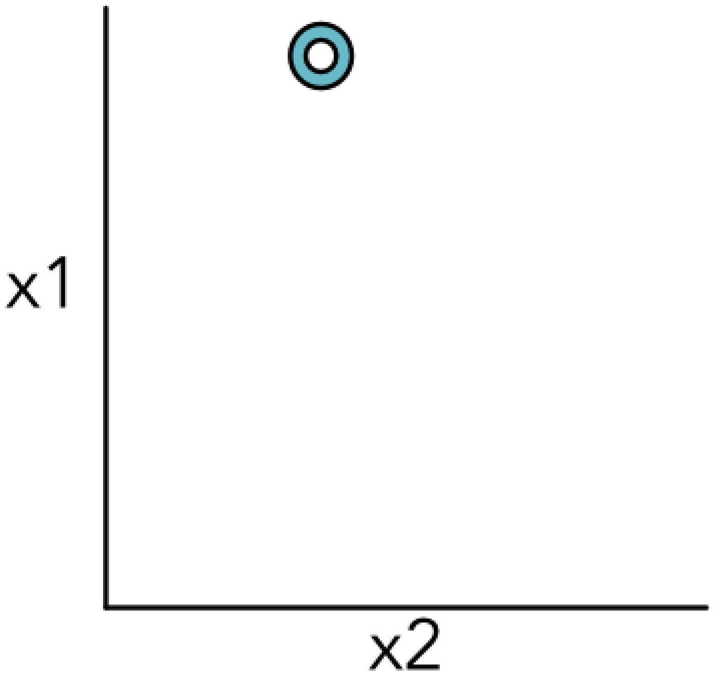


Data Labels



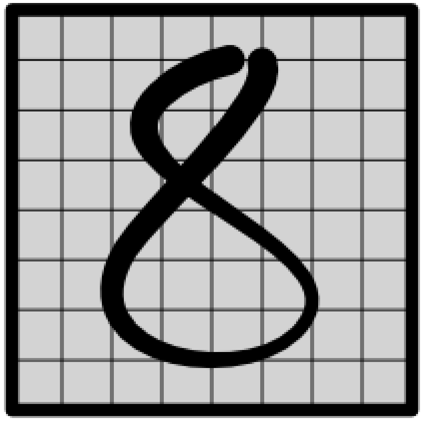


Data Points



Strategy

Build a neural network to classify these



Problem Setup

- Training: Exactly the same as simple
- Loss: Exactly the same as simple
- Models: Mostly similar to the simple problem.

Challenges

1) How do we handle input features? 2) How do we look at variable-size areas? 3) How do we predict multiple labels?

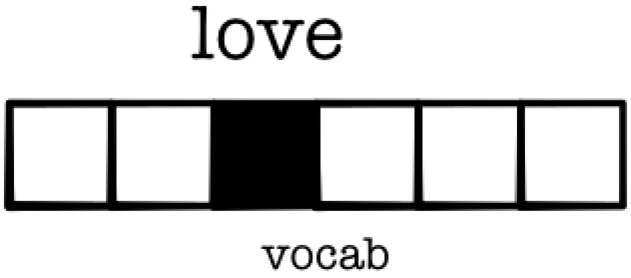
Basic NLP

Network Challenges

- Converting words to tensors
- Converting sentences to tensors
- Handling word combinations

What is a word?

- Treat words as index in vocabulary
- Represent as a one-hot vector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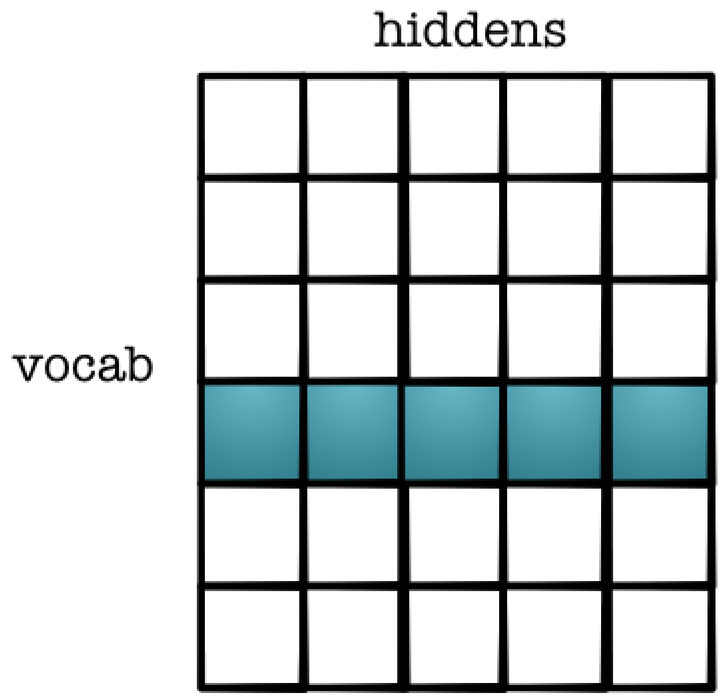
One-Hot Issue

- Tens of thousands of words
- Opposite problem as before, 2-features to 10,000
- ``Embedding'' represent high-dim space in low dim

embeddings



Intuition: Lookup in Table

Get word vector

```
VOCAB = 1000
EMB = 100
embeddings = rand(EMB, VOCAB)
word = 20
embeddings[0, word]


# * Challenge:  How to compute `backward`
```

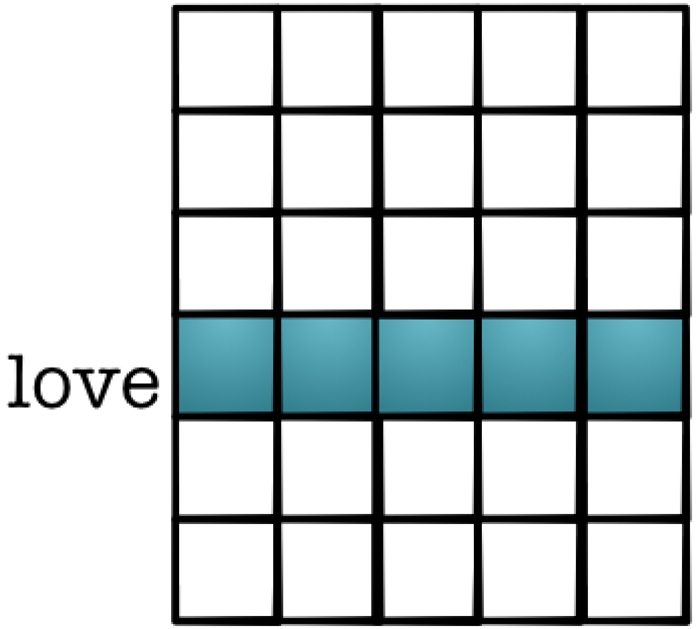
```
0.7649509638874962
```

Alternative: Lookup by broadcast

Get word vector

```
# word_one_hot = tensor([0 if i != word else 1
#                        for i in range(VOCAB)])
# embeddings @ word_one_hot.view(VOCAB, 1)
```

embeddings



How does this share information?

- Similar words have similar embedding dim
- Dot-product - easy way to tell similarity

```
(word_emb1 * word_emb2).sum()
```

- Differentiable!

Embedding Layer

Easy to write as a layer

```
class Embedding(minitorch.Module):
    def __init__(self, vocab_size, emb_size):
        super().__init__()
        self.weights = \
            minitorch.Parameter(minitorch.rand((vocab_size, emb_size)))
        self.vocab_size = vocab_size

    def forward(input):
        return (input @ self.weights.values)
```

Where do these come from?

- Trained from a different model
- Extracted and posted to use
- (Many more details in NLP class)

Examples

Embeddings

```
embedding.weights.value.update(pretrained_weights)
```

- https://projector.tensorflow.org/

Examples

Query 1

```
^(lisbon|portugal|america|washington|rome|athens|london|england|greece|italy)$
```

Query 2

```
^(doctor|patient|lawyer|client|clerk|customer|author|reader)$
```

Challenge 2: Sentence Length

- Examples may be of different length
- Need to all be converted to vectors and utilized

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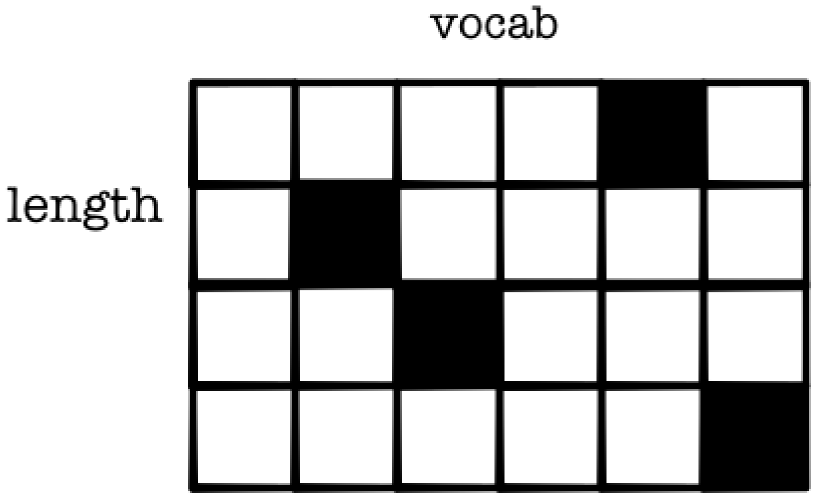

Value Transformation

- batch x length x vocab
- batch x length x feature
- batch x feature
- batch x hidden
- batch

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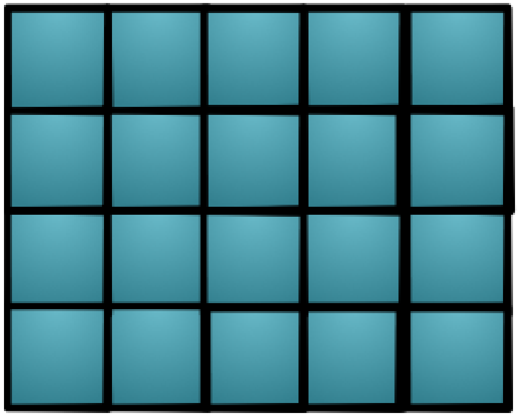

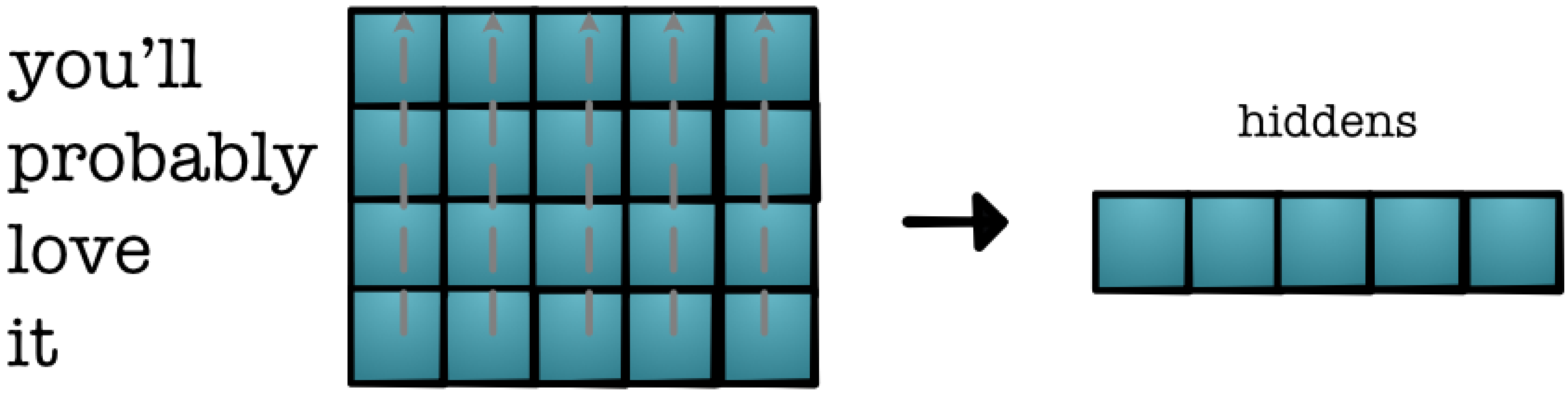
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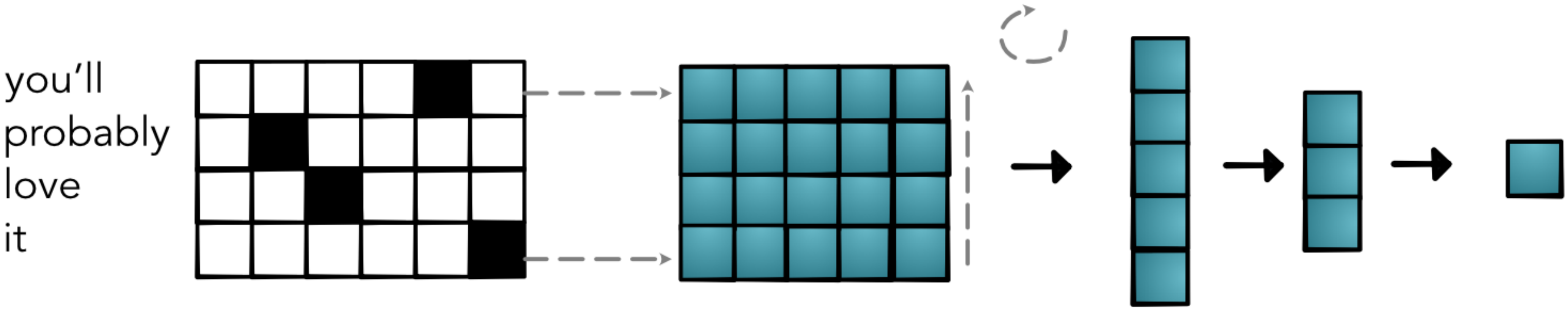
Benefits

- Extremely simple
- Embeddings encode key information
- Have all the tools we need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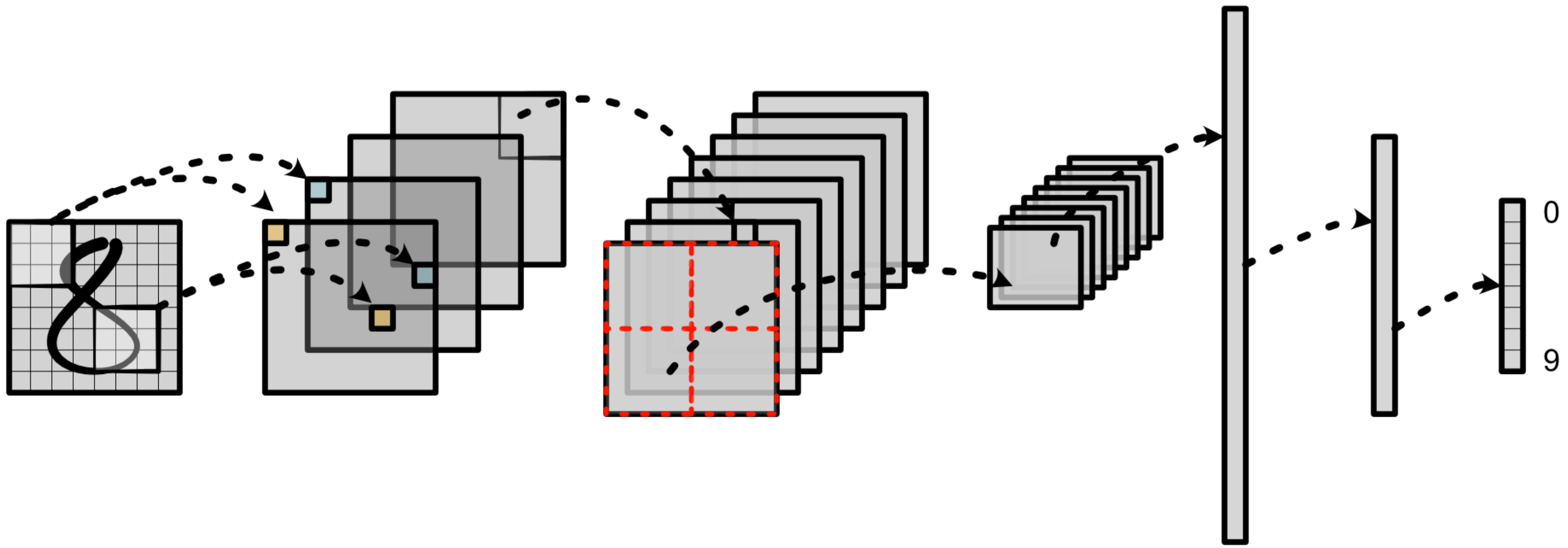
Issues

- Completely ignores relative order
- Completley ignores absolute order
- Embeddings for all words, even rare ones

Basic Recognition

Challenges

- Converting images to tensors
- Handling different scales
- Multiclass prediction.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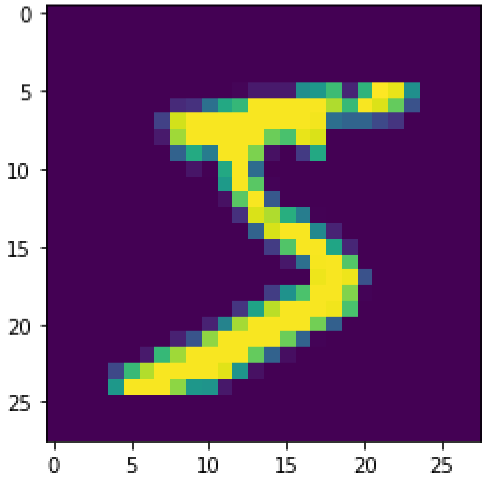
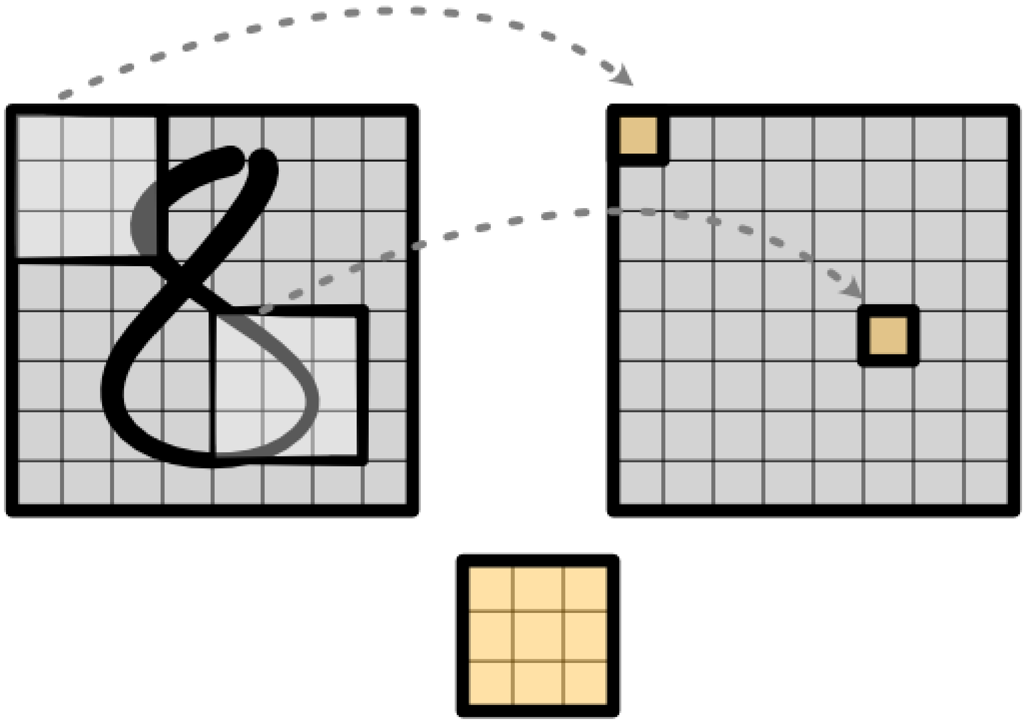
Challenge 1: Input Representation

link

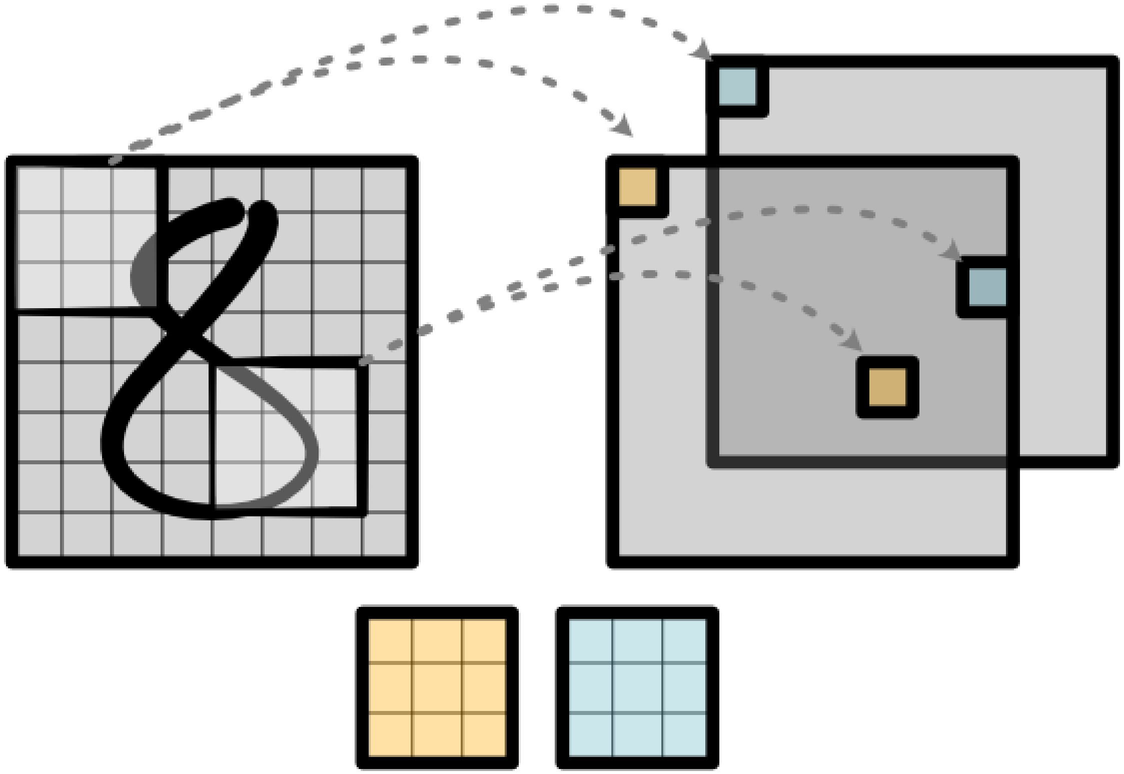
Challenge 1: Input Representation



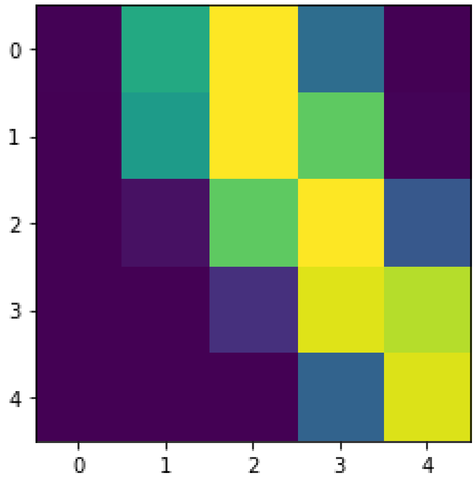
Challenge 1: Input Features

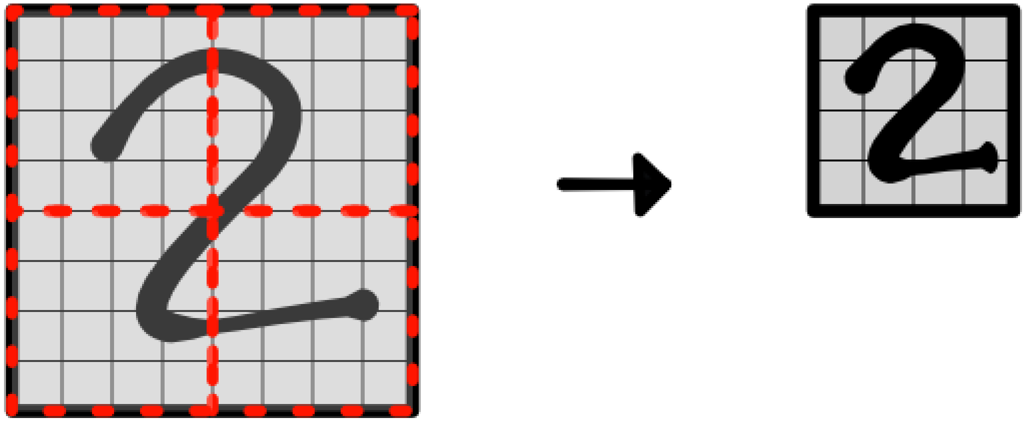


Challenge 1: Input Features



Challenge 1: Input Representation





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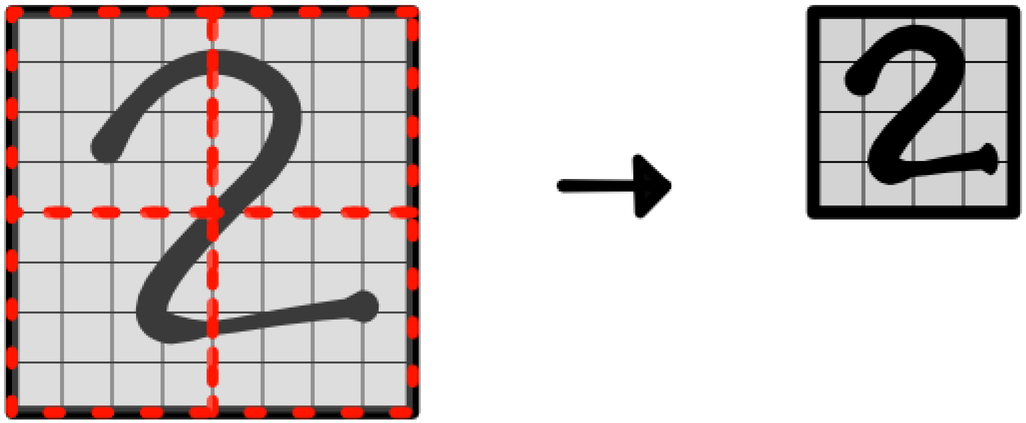

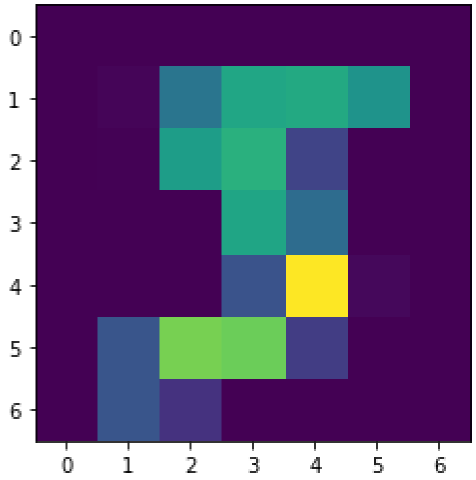

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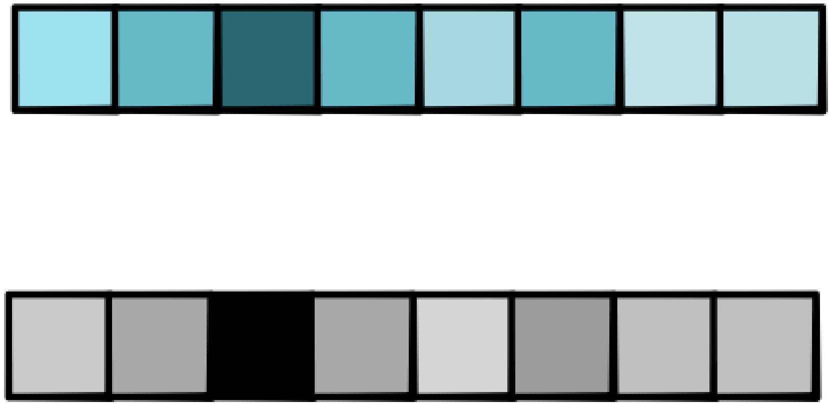

Challenge 3: Multiple Output