Test

November 13, 2024

[35]:

```python
# Add the Model Scripts folder to the path
import sys
sys.path.append("Model Scripts")
sys.path.append("Model Weights")


# Import the necessary libraries
import torch
import random
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
```

[36]:

```python
# Import the function to create the model
from Scripts.ArithmeticTransformer import create_arithmetic_transformer

# Create a model with default parameters
model = create_arithmetic_transformer()

# Or create a model with custom parameters
model = create_arithmetic_transformer(
    vocab_size=14,
    embed_size=128,
    num_heads=4,
    ff_dim=512,
    num_layers=3,
    max_length=64
)
```

[37]:

```python
import torch

def load_model(model_path, device=None):
    # Determine device
    if device is None:
        device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
```

```python
    # Load checkpoint
    print(f"Loading model on {device}")
    checkpoint = torch.load(model_path, map_location=device)

    # Extract config
    config = checkpoint['model_config']
    print("Model configuration:", config)

    # Create model
    model = create_arithmetic_transformer(
        vocab_size=config['vocab_size'],
        embed_size=config['embed_size'],
        num_heads=config['num_heads'],
        ff_dim=config['ff_dim'],
        num_layers=config['num_layers'],
        max_length=config['max_length'],
        dropout=config['dropout']
    )

    # Load state dict
    model.load_state_dict(checkpoint['model_state_dict'])

    # Move model to device and set to eval mode
    model = model.to(device)
    model.eval()

    # Get vocab if available
    vocab = checkpoint.get('vocab')
    inv_vocab = checkpoint.get('inv_vocab')

    print(f"Model loaded successfully! Best accuracy: {checkpoint['accuracy']:.
↪4f}")

    return model, vocab, inv_vocab, device, config

# Usage:
model_path = './Weights/large_addition_model.pth'
model, vocab, inv_vocab, device, config = load_model(model_path)
```

```
Loading model on cpu
Model configuration: {'vocab_size': 14, 'embed_size': 512, 'num_heads': 8,
'ff_dim': 2048, 'num_layers': 8, 'max_length': 42, 'dropout': 0.15}
Model loaded successfully! Best accuracy: 1.0000
```

[38]:
```python
# If you need to use the model for inference, you'll want these helper␣
↪functions:
def preprocess_input(input_str, max_length, vocab):
```

```python
    # Reverse the input string
    input_str = input_str[::-1]
    # Tokenize
    tokens = [vocab[c] for c in input_str if c in vocab]
    # Pad
    padded = tokens + [vocab['<PAD>']] * (max_length - len(tokens))
    return torch.tensor(padded).unsqueeze(0)  # Add batch dimension

def decode_output(output_tensor, inv_vocab):
    _, predicted = output_tensor.max(2)
    decoded = []
    for token in predicted[0]:
        token_val = token.item()
        if token_val == vocab['<EOS>']:
            break
        if token_val != vocab['<PAD>']:
            decoded.append(inv_vocab[token_val])
    return ''.join(decoded)[::-1]  # Reverse at the end

# Example usage:
def test_addition(num1, num2, model, vocab, inv_vocab, max_length):
    input_str = f"{num1}+{num2}="
    input_tensor = preprocess_input(input_str, max_length, vocab)
    with torch.no_grad():
        output = model(input_tensor)
        result = decode_output(output, inv_vocab)
    print(f"{num1} + {num2} = {result}")
    print(f"Correct result: {num1 + num2}")
    print(f"Model's prediction is {'correct' if int(result) == num1 + num2 else␣
 ↪'incorrect'}")
```

[39]:
```python
# Test a simple addition
test_addition(123, 456, model, vocab, inv_vocab, config['max_length'])

# or test multiple additions in a loop
test_cases = [
    (5, 7),
    (42, 58),
    (123, 456),
    (1234, 5678)
]

for num1, num2 in test_cases:
    test_addition(num1, num2, model, vocab, inv_vocab, config['max_length'])
```

```
123 + 456 = 579
Correct result: 579
Model's prediction is correct
```

```
5 + 7 = 12
Correct result: 12
Model's prediction is correct
42 + 58 = 100
Correct result: 100
Model's prediction is correct
123 + 456 = 579
Correct result: 579
Model's prediction is correct
1234 + 5678 = 6912
Correct result: 6912
Model's prediction is correct
```

[40]:

```python
  # Test a simple addition
test_addition(123, 456, model, vocab, inv_vocab, config['max_length'])

# or test multiple additions in a loop
test_cases = [
    (5, 7),
    (42, 58),
    (123, 456),
    (1234, 5678),
    (10304923, 123123123),
    (123123123, 10304923)

]

for num1, num2 in test_cases:
    test_addition(num1, num2, model, vocab, inv_vocab, config['max_length'])
```

```
123 + 456 = 579
Correct result: 579
Model's prediction is correct
5 + 7 = 12
Correct result: 12
Model's prediction is correct
42 + 58 = 100
Correct result: 100
Model's prediction is correct
123 + 456 = 579
Correct result: 579
Model's prediction is correct
1234 + 5678 = 6912
Correct result: 6912
Model's prediction is correct
10304923 + 123123123 = 133428046
Correct result: 133428046
Model's prediction is correct
```

```
123123123 + 10304923 = 133428046
Correct result: 133428046
Model's prediction is correct
```

[41]:
```python
import torch
import numpy as np
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
from collections import defaultdict
import seaborn as sns
import random

class ArithmeticModelTester:
    def __init__(self, model, vocab, inv_vocab, max_seq_length):
        self.model = model
        self.vocab = vocab
        self.inv_vocab = inv_vocab
        self.max_seq_length = max_seq_length
        self.model.eval()
        self.results = defaultdict(dict)

    def preprocess_input(self, input_str):
        """Preprocess input string for model"""
        input_str = input_str[::-1]  # Reverse string
        tokens = [self.vocab[c] for c in input_str if c in self.vocab]
        padded = tokens + [self.vocab['<PAD>']] * (self.max_seq_length -␣
↪len(tokens))
        return torch.tensor(padded).unsqueeze(0)

    def decode_output(self, output_tensor):
        """Decode model output"""
        _, predicted = output_tensor.max(2)
        decoded = []
        for token in predicted[0]:
            token_val = token.item()
            if token_val == self.vocab['<EOS>']:
                break
            if token_val != self.vocab['<PAD>']:
                decoded.append(self.inv_vocab[token_val])
        return ''.join(decoded)[::-1]

    def test_single_digits(self, num_trials=100):
        """Test single digit additions"""
        correct = 0
        for _ in range(num_trials):
            n1 = random.randint(0, 9)
            n2 = random.randint(0, 9)
```

```python
            result = self.predict_addition(n1, n2)
            if result == n1 + n2:
                correct += 1
        self.results['single_digits'] = {'accuracy': correct/num_trials}
        return correct/num_trials

    def test_commutative_property(self, max_digit=999, num_trials=100):
        """Test if a + b == b + a"""
        correct = 0
        for _ in range(num_trials):
            n1 = random.randint(0, max_digit)
            n2 = random.randint(0, max_digit)
            result1 = self.predict_addition(n1, n2)
            result2 = self.predict_addition(n2, n1)
            if result1 == result2 == (n1 + n2):
                correct += 1
        self.results['commutative'] = {'accuracy': correct/num_trials}
        return correct/num_trials

    def test_zero_property(self, max_digit=999, num_trials=100):
        """Test additions with zero"""
        correct = 0
        for _ in range(num_trials):
            n = random.randint(0, max_digit)
            result1 = self.predict_addition(n, 0)
            result2 = self.predict_addition(0, n)
            if result1 == result2 == n:
                correct += 1
        self.results['zero_property'] = {'accuracy': correct/num_trials}
        return correct/num_trials

    def test_by_length(self, max_length=5):
        """Test additions with different number lengths"""
        results = {}
        for length in range(1, max_length + 1):
            correct = 0
            trials = 100
            for _ in range(trials):
                n1 = random.randint(10**(length-1), 10**length - 1)
                n2 = random.randint(10**(length-1), 10**length - 1)
                result = self.predict_addition(n1, n2)
                if result == n1 + n2:
                    correct += 1
            results[length] = correct/trials
        self.results['length_wise'] = results
        return results
```

```python
    def test_carries(self):
        """Test additions requiring different numbers of carries"""
        test_cases = [
            (9, 1),       # Single carry
            (99, 1),      # Double carry
            (999, 1),     # Triple carry
            (19, 81),     # Multiple carries
            (999999, 1)   # Many carries
        ]
        results = {}
        for n1, n2 in test_cases:
            result = self.predict_addition(n1, n2)
            results[f"{n1}+{n2}"] = result == n1 + n2
        self.results['carries'] = results
        return results

    def predict_addition(self, n1, n2):
        """Make a prediction for n1 + n2"""
        input_str = f"{n1}+{n2}="
        input_tensor = self.preprocess_input(input_str)
        with torch.no_grad():
            output = self.model(input_tensor)
            result_str = self.decode_output(output)
            try:
                return int(result_str)
            except ValueError:
                return None

    def visualize_results(self):
        """Visualize test results"""
        plt.figure(figsize=(15, 10))

        # Plot accuracy by number length
        if 'length_wise' in self.results:
            plt.subplot(2, 2, 1)
            lengths = list(self.results['length_wise'].keys())
            accuracies = list(self.results['length_wise'].values())
            plt.plot(lengths, accuracies, marker='o')
            plt.title('Accuracy by Number Length')
            plt.xlabel('Number Length (digits)')
            plt.ylabel('Accuracy')

        # Plot bar chart of different properties
        properties = ['single_digits', 'commutative', 'zero_property']
        accuracies = [self.results[prop]['accuracy'] for prop in properties if
 prop in self.results]
        if accuracies:
```

```
            plt.subplot(2, 2, 2)
            plt.bar(properties, accuracies)
            plt.title('Accuracy by Property')
            plt.xticks(rotation=45)
            plt.ylabel('Accuracy')

        plt.tight_layout()
        plt.show()

# Example usage:
"""
# Load your model and necessary components
model = load_model('path_to_model.pth')
vocab = {...}  # Your vocabulary
inv_vocab = {...}  # Inverse vocabulary
max_seq_length = 42  # Your max sequence length

# Create tester instance
tester = ArithmeticModelTester(model, vocab, inv_vocab, max_seq_length)

# Run tests
tester.test_single_digits()
tester.test_commutative_property()
tester.test_zero_property()
tester.test_by_length()
tester.test_carries()

# Visualize results
tester.visualize_results()
"""
```

[41]:

```
"\n# Load your model and necessary components\nmodel =
load_model('path_to_model.pth')\nvocab = {…}  # Your vocabulary\ninv_vocab =
{…}  # Inverse vocabulary\nmax_seq_length = 42  # Your max sequence
length\n\n# Create tester instance\ntester = ArithmeticModelTester(model, vocab,
inv_vocab, max_seq_length)\n\n# Run tests\ntester.test_single_digits()\ntester.t
est_commutative_property()\ntester.test_zero_property()\ntester.test_by_length()
\ntester.test_carries()\n\n# Visualize results\ntester.visualize_results()\n"
```

[45]:

```
import torch
import numpy as np
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
import random
import pandas as pd
```

```python
from datetime import datetime

class ModelEvaluator:
    def __init__(self, model, vocab, inv_vocab, max_seq_length, random_seed=42):
        """
        Initialize evaluator with model and set random seed for reproducibility
        """
        self.model = model
        self.vocab = vocab
        self.inv_vocab = inv_vocab
        self.max_seq_length = max_seq_length
        self.model.eval()

        # Set random seeds for reproducibility
        torch.manual_seed(random_seed)
        np.random.seed(random_seed)
        random.seed(random_seed)

        # Store test configuration
        self.test_config = {
            'random_seed': random_seed,
            'timestamp': datetime.now().strftime('%Y-%m-%d_%H-%M-%S'),
            'max_seq_length': max_seq_length
        }

    def generate_test_case(self, min_digits=1, max_digits=20):
        """Generate a random test case with specified digit length range"""
        len1 = random.randint(min_digits, max_digits)
        len2 = random.randint(min_digits, max_digits)

        num1 = random.randint(10**(len1-1), 10**len1 - 1)
        num2 = random.randint(10**(len2-1), 10**len2 - 1)

        return num1, num2, len1, len2

    def preprocess_input(self, input_str):
        """Preprocess input string for model"""
        input_str = input_str[::-1]  # Reverse string
        tokens = [self.vocab[c] for c in input_str if c in self.vocab]
        padded = tokens + [self.vocab['<PAD>']] * (self.max_seq_length -␣
↪len(tokens))
        return torch.tensor(padded).unsqueeze(0)

    def decode_output(self, output_tensor):
        """Decode model output"""
        _, predicted = output_tensor.max(2)
        decoded = []
```

```python
        for token in predicted[0]:
            token_val = token.item()
            if token_val == self.vocab['<EOS>']:
                break
            if token_val != self.vocab['<PAD>']:
                decoded.append(self.inv_vocab[token_val])
        return ''.join(decoded)[::-1]

    def evaluate_model(self, num_samples=10000):
        """
        Evaluate model on random test cases and collect detailed metrics
        """
        results = []

        for _ in tqdm(range(num_samples), desc="Evaluating Model"):
            # Generate test case
            num1, num2, len1, len2 = self.generate_test_case()
            true_result = num1 + num2

            # Get model prediction
            input_str = f"{num1}+{num2}="
            input_tensor = self.preprocess_input(input_str)

            with torch.no_grad():
                output = self.model(input_tensor)
                pred_str = self.decode_output(output)

            try:
                pred_result = int(pred_str)
                is_correct = pred_result == true_result
            except ValueError:
                pred_result = None
                is_correct = False

            # Collect detailed information about this test case
            results.append({
                'num1': num1,
                'num2': num2,
                'len1': len1,
                'len2': len2,
                'max_len': max(len1, len2),
                'total_len': len1 + len2,
                'true_result': true_result,
                'predicted_result': pred_result,
                'is_correct': is_correct,
                'carries': self.count_carries(num1, num2)
            })
```

```python
        return pd.DataFrame(results)

    def count_carries(self, num1, num2):
        """Count the number of carry operations in addition"""
        carry = 0
        carries = 0

        while num1 > 0 or num2 > 0 or carry:
            digit1 = num1 % 10
            digit2 = num2 % 10

            if digit1 + digit2 + carry >= 10:
                carries += 1
                carry = 1
            else:
                carry = 0

            num1 //= 10
            num2 //= 10

        return carries

    def analyze_results(self, df):
        """
        Analyze results and generate comprehensive metrics
        """
        metrics = {
            'test_config': self.test_config,
            'overall_accuracy': df['is_correct'].mean(),
            'total_samples': len(df),
            'metrics_by_length': {},
            'metrics_by_carries': {}
        }

        # Analyze by maximum length of operands
        for length in range(1, 21):
            length_df = df[df['max_len'] == length]
            if len(length_df) > 0:
                metrics['metrics_by_length'][length] = {
                    'accuracy': length_df['is_correct'].mean(),
                    'samples': len(length_df)
                }

        # Analyze by number of carries
        for carries in df['carries'].unique():
            carries_df = df[df['carries'] == carries]
```

```
            metrics['metrics_by_carries'][int(carries)] = {
                'accuracy': carries_df['is_correct'].mean(),
                'samples': len(carries_df)
            }

        return metrics

    def visualize_results(self, df, metrics):
        """
        Create visualizations of model performance
        """
        plt.figure(figsize=(20, 10))

        # Plot 1: Accuracy by maximum length
        plt.subplot(2, 2, 1)
        lengths = list(metrics['metrics_by_length'].keys())
        accuracies = [metrics['metrics_by_length'][l]['accuracy'] for l in␣
↪lengths]
        plt.plot(lengths, accuracies, marker='o')
        plt.title('Accuracy by Maximum Length of Operands')
        plt.xlabel('Maximum Length (digits)')
        plt.ylabel('Accuracy')

        # Plot 2: Accuracy by number of carries
        plt.subplot(2, 2, 2)
        carries = list(metrics['metrics_by_carries'].keys())
        carry_accuracies = [metrics['metrics_by_carries'][c]['accuracy'] for c␣
↪in carries]
        plt.plot(carries, carry_accuracies, marker='o', color='orange')
        plt.title('Accuracy by Number of Carries')
        plt.xlabel('Number of Carries')
        plt.ylabel('Accuracy')

        # Plot 3: Distribution of test cases
        plt.subplot(2, 2, 3)
        sns.histplot(data=df, x='max_len', bins=20)
        plt.title('Distribution of Test Cases by Maximum Length')
        plt.xlabel('Maximum Length (digits)')

        # Plot 4: Heatmap of length combinations
        plt.subplot(2, 2, 4)
        heatmap_data = pd.crosstab(df['len1'], df['len2'])
        sns.heatmap(heatmap_data, cmap='YlOrRd')
        plt.title('Distribution of Length Combinations')
        plt.xlabel('Length of Second Number')
        plt.ylabel('Length of First Number')
```

```
        plt.tight_layout()
        plt.show()

        # Print summary statistics
        print("\nSummary Statistics:")
        print(f"Overall Accuracy: {metrics['overall_accuracy']:.4f}")
        print(f"Total Samples: {metrics['total_samples']}")
```

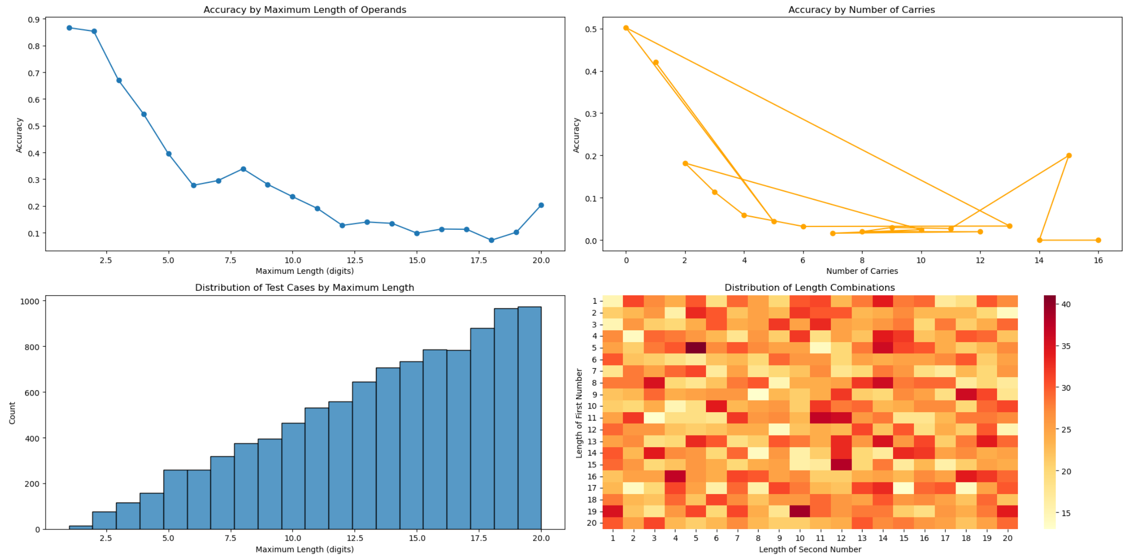
[ ]:
```
import torch
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
import random
import pandas as pd
from datetime import datetime

# Recreate the model architecture (you'll need to import your model class)
from Scripts.ArithmeticTransformer import *


# First, let's load the model correctly
def load_model_and_config(model_path):
    """Load the model and its configuration"""
    # Load checkpoint
    print(f"Loading model on {device}")
    checkpoint = torch.load(model_path, map_location=device)

    # Extract config
    config = checkpoint['model_config']
    print("Model configuration:", config)

    # Create model
    model = create_arithmetic_transformer(
        vocab_size=config['vocab_size'],
        embed_size=config['embed_size'],
        num_heads=config['num_heads'],
        ff_dim=config['ff_dim'],
        num_layers=config['num_layers'],
        max_length=config['max_length'],
        dropout=config['dropout']
    )

    # Load state dict
    model.load_state_dict(checkpoint['model_state_dict'])

    # Move model to device and set to eval mode
```

```
    model = model.to(device)
    model.eval()

    # Get vocab if available
    vocab = checkpoint.get('vocab')
    inv_vocab = checkpoint.get('inv_vocab')

    print(f"Model loaded successfully! Best accuracy: {checkpoint['accuracy']:.
 ↪4f}")

    return model, vocab, inv_vocab, config['max_length']

# [Previous ModelEvaluator class code remains the same]
```

[52]:
```
# SMALL MODEL EVALUATION
# Load model and components
model_path = './Weights/small_addition_model.pth'  # Update with your model path
model, vocab, inv_vocab, max_seq_length = load_model_and_config(model_path)

# Create evaluator with specific random seed
evaluator = ModelEvaluator(model, vocab, inv_vocab, max_seq_length,␣
 ↪random_seed=42)

# Run evaluation
results_df = evaluator.evaluate_model(num_samples=10000)z
metrics = evaluator.analyze_results(results_df)

# Visualize results
evaluator.visualize_results(results_df, metrics)

# Save results
timestamp = datetime.now().strftime('%Y-%m-%d_%H-%M-%S')
results_df.to_csv(f'model_evaluation_{timestamp}.csv')

# Print some interesting statistics
print("\nDetailed Statistics:")
print(f"Number of correct predictions: {results_df['is_correct'].sum()}")
print(f"Average number of carries: {results_df['carries'].mean():.2f}")

# Print performance by length ranges
print("\nPerformance by length ranges:")
length_ranges = [(1,5), (6,10), (11,15), (16,20)]
for start, end in length_ranges:
    mask = (results_df['max_len'] >= start) & (results_df['max_len'] <= end)
    acc = results_df[mask]['is_correct'].mean()
    print(f"{start}-{end} digits: {acc:.4f}")
```

```
Loading model on cpu
```

```
Model configuration: {'vocab_size': 14, 'embed_size': 64, 'num_heads': 2,
'ff_dim': 256, 'num_layers': 2, 'max_length': 42, 'dropout': 0.1}
Model loaded successfully! Best accuracy: 0.7937

Evaluating Model: 100%|      | 10000/10000 [00:44<00:00, 222.32it/s]
```




```
Summary Statistics:
Overall Accuracy: 0.1820
Total Samples: 10000

Detailed Statistics:
Number of correct predictions: 1820
Average number of carries: 3.65

Performance by length ranges:
1-5 digits: 0.5507
6-10 digits: 0.2826
11-15 digits: 0.1351
16-20 digits: 0.1221
```

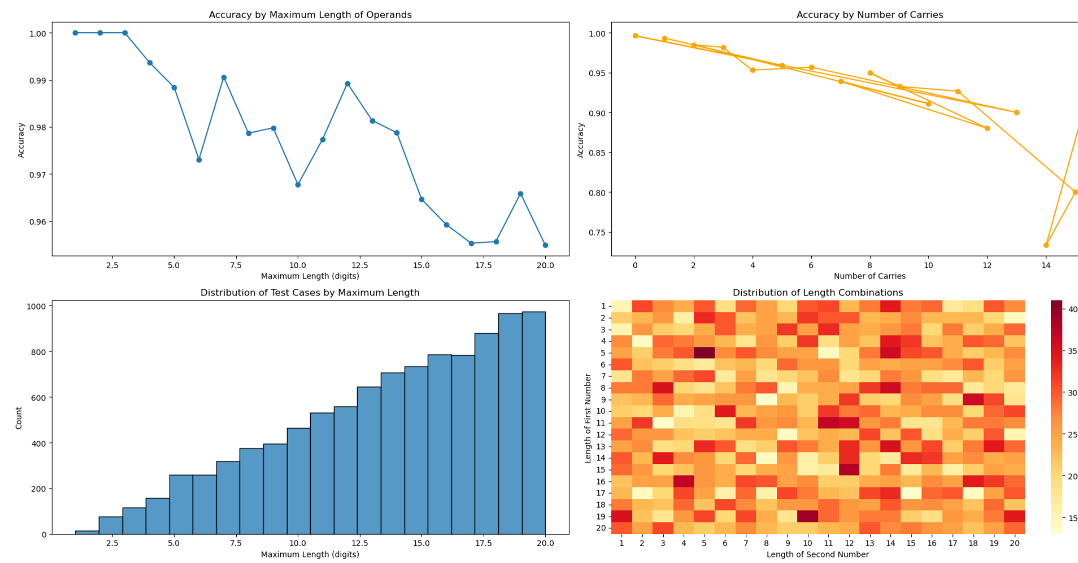
[51]:

```
# MEDUIM MODEL EVALUATION
# Load model and components
model_path = './Weights/medium_addition_model.pth'  # Update with your model␣
↪path
model, vocab, inv_vocab, max_seq_length = load_model_and_config(model_path)

# Create evaluator with specific random seed
```

```python
evaluator = ModelEvaluator(model, vocab, inv_vocab, max_seq_length,␣
↪random_seed=42)

# Run evaluation
results_df = evaluator.evaluate_model(num_samples=10000)
metrics = evaluator.analyze_results(results_df)

# Visualize results
evaluator.visualize_results(results_df, metrics)

# Save results
timestamp = datetime.now().strftime('%Y-%m-%d_%H-%M-%S')
results_df.to_csv(f'model_evaluation_{timestamp}.csv')

# Print some interesting statistics
print("\nDetailed Statistics:")
print(f"Number of correct predictions: {results_df['is_correct'].sum()}")
print(f"Average number of carries: {results_df['carries'].mean():.2f}")

# Print performance by length ranges
print("\nPerformance by length ranges:")
length_ranges = [(1,5), (6,10), (11,15), (16,20)]
for start, end in length_ranges:
    mask = (results_df['max_len'] >= start) & (results_df['max_len'] <= end)
    acc = results_df[mask]['is_correct'].mean()
    print(f"{start}-{end} digits: {acc:.4f}")
```

```
Loading model on cpu
Model configuration: {'vocab_size': 14, 'embed_size': 256, 'num_heads': 4,
'ff_dim': 1024, 'num_layers': 4, 'max_length': 42, 'dropout': 0.1}
Model loaded successfully! Best accuracy: 0.9987
```

```
Evaluating Model: 100%|          | 10000/10000 [01:44<00:00, 96.03it/s]
```



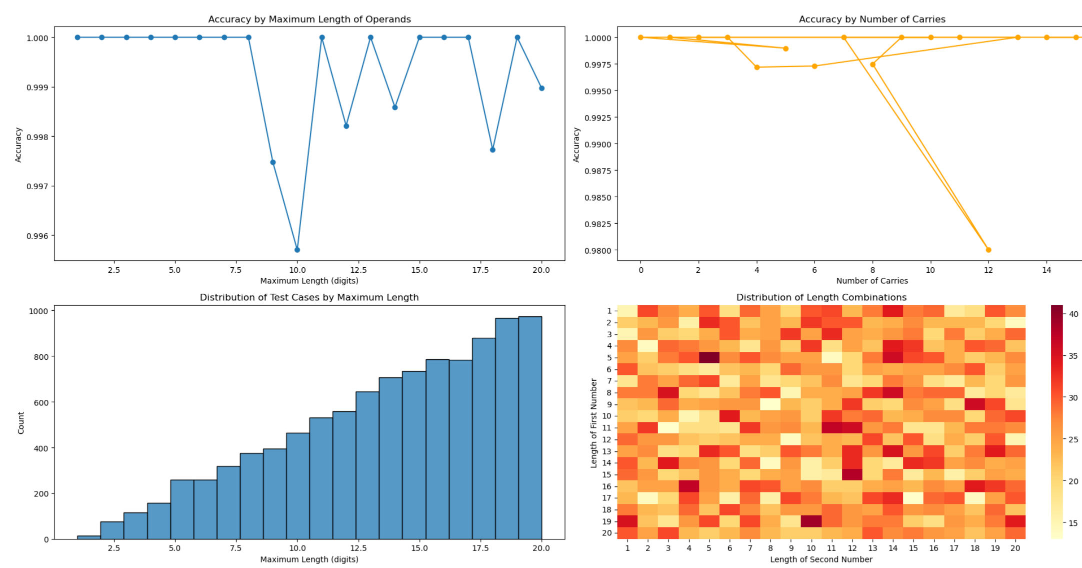

```
Summary Statistics:
Overall Accuracy: 0.9701
Total Samples: 10000

Detailed Statistics:
Number of correct predictions: 9701
Average number of carries: 3.65

Performance by length ranges:
1-5 digits: 0.9936
6-10 digits: 0.9774
11-15 digits: 0.9776
16-20 digits: 0.9583
```

[53]:

```python
# LARGE MODEL EVALUATION
# Load model and components
model_path = './Weights/large_addition_model.pth'  # Update with your model path
model, vocab, inv_vocab, max_seq_length = load_model_and_config(model_path)

# Create evaluator with specific random seed
evaluator = ModelEvaluator(model, vocab, inv_vocab, max_seq_length,
    random_seed=42)

# Run evaluation
results_df = evaluator.evaluate_model(num_samples=10000)
metrics = evaluator.analyze_results(results_df)

# Visualize results
```

```python
evaluator.visualize_results(results_df, metrics)

# Save results
timestamp = datetime.now().strftime('%Y-%m-%d_%H-%M-%S')
results_df.to_csv(f'model_evaluation_{timestamp}.csv')

# Print some interesting statistics
print("\nDetailed Statistics:")
print(f"Number of correct predictions: {results_df['is_correct'].sum()}")
print(f"Average number of carries: {results_df['carries'].mean():.2f}")

# Print performance by length ranges
print("\nPerformance by length ranges:")
length_ranges = [(1,5), (6,10), (11,15), (16,20)]
for start, end in length_ranges:
    mask = (results_df['max_len'] >= start) & (results_df['max_len'] <= end)
    acc = results_df[mask]['is_correct'].mean()
    print(f"{start}-{end} digits: {acc:.4f}")
```

```
Loading model on cpu
Model configuration: {'vocab_size': 14, 'embed_size': 512, 'num_heads': 8,
'ff_dim': 2048, 'num_layers': 8, 'max_length': 42, 'dropout': 0.15}
Model loaded successfully! Best accuracy: 1.0000

Evaluating Model: 100%|      | 10000/10000 [13:21<00:00, 12.47it/s]
```




```
Summary Statistics:
Overall Accuracy: 0.9992
Total Samples: 10000
```

```
Detailed Statistics:
Number of correct predictions: 9992
Average number of carries: 3.65

Performance by length ranges:
1-5 digits: 1.0000
6-10 digits: 0.9983
11-15 digits: 0.9994
16-20 digits: 0.9993
```

[ ]: