CSCI S-89B — Assignment 3

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Problem 1 (25 points)

(a) Load and preprocess the text (tokenization, stemming, lemmatization)

Methods: NLTK `word_tokenize`, `PorterStemmer`, `WordNetLemmatizer(pos='v')`.
If SpaCy is available, `en_core_web_sm` lemmatization is additionally shown.

In [54]:
```
# Problem 1-(a)
import nltk, sys
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer, WordNetLemmatizer
nltk.download('punkt', quiet=True); nltk.download('wordnet', quiet=True)

text = (
    "Urban delivery robots operate on sidewalks where pedestrians, pets, and bic
    "During peak hours, a robot must plan short detours, yield at crossings, and
    "Well-designed policies improve safety and keep travel times predictable for
)

# NLTK
tokens_nltk = word_tokenize(text)
porter = PorterStemmer()
stems_nltk = [porter.stem(w) for w in tokens_nltk]
wnl = WordNetLemmatizer()
lemmas_nltk_v = [wnl.lemmatize(w, pos='v') for w in tokens_nltk]

# SpaCy
lemmas_spacy = None
try:
    import spacy
    nlp = spacy.load("en_core_web_sm")
    lemmas_spacy = [t.lemma_ for t in nlp(text)]
except Exception:
    lemmas_spacy = None

print("NLTK tokens (first 15):", tokens_nltk[:15])
print("NLTK stems (first 15):", stems_nltk[:15])
print("NLTK lemmas (verb POS, first 15):", lemmas_nltk_v[:15])
print("SpaCy lemmas (first 15):", (lemmas_spacy[:15] if lemmas_spacy else "N/A")
```

```
NLTK tokens (first 15): ['Urban', 'delivery', 'robots', 'operate', 'on', 'sidewal
ks', 'where', 'pedestrians', ',', 'pets', ',', 'and', 'bicycles', 'share', 'spac
e']
NLTK stems (first 15): ['urban', 'deliveri', 'robot', 'oper', 'on', 'sidewalk',
'where', 'pedestrian', ',', 'pet', ',', 'and', 'bicycl', 'share', 'space']
NLTK lemmas (verb POS, first 15): ['Urban', 'delivery', 'robots', 'operate', 'o
n', 'sidewalks', 'where', 'pedestrians', ',', 'pet', ',', 'and', 'bicycle', 'shar
e', 'space']
SpaCy lemmas (first 15): ['urban', 'delivery', 'robot', 'operate', 'on', 'sidewal
k', 'where', 'pedestrian', ',', 'pet', ',', 'and', 'bicycle', 'share', 'space']
```

(b) Comparison

NLTK stemming is rule-based and may yield non-words (*operate* → *oper*, *bicycles* → *bicycl*), while lemmatization returns base forms given POS (*bicycles* → *bicycle*). Tokenization differs slightly in punctuation handling. SpaCy infers POS automatically and typically produces cleaner lemmas without manual POS flags.

For example, in our sample text:

- NLTK Porter stemmed *bicycles* → *bicycl* (non-word).
- NLTK WordNet lemmatizer returned *bicycles* → *bicycle*.
- SpaCy also returned *bicycle*.

This illustrates the difference in linguistic accuracy.

(c) Importance

Tokenization defines model inputs. Stemming/lemmatization reduce sparsity and improve generalization in classical pipelines (e.g., BoW, n-grams). Choice depends on tolerance for non-words (stemming) vs. linguistic correctness (lemmatization).

Problem 2 (25 points)

(a) Tokenize and lemmatize large and small texts

Preprocessing: `word_tokenize → lowercase → cleanup → WordNetLemmatizer(pos='v')` .

In [55]:
```
# Problem 2-(a)
import re
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer

# Base paragraph (original).
big_base = (
    "Teams translate raw logs into stable tables that reflect growth, retention,
    "Proposed changes ship to small traffic, expand if guardrails hold, and roll
    "Quantitative dashboards are paired with qualitative research to surface fri
    "Data hygiene—versioned events, documented thresholds, and planned schema mi
)
# Repeat to ensure large vocabulary; adjust the factor if needed.
big_text = " ".join([big_base for _ in range(60)])
```

```
small_text = (
    "During the spring launch, engineers orchestrated pilot rollouts and shadow
    "They stress-tested edge conditions, calibrated sensors under hailstorms, an
    "that surfaced only on rural backroads."
)

def normalize_lemmatize(s: str):
    toks = [t.lower() for t in word_tokenize(s)]
    toks = [re.sub(r"[^a-z0-9']", "", t) for t in toks]
    toks = [t for t in toks if t]
    wnl = WordNetLemmatizer()
    return [wnl.lemmatize(t, pos='v') for t in toks]

big_tokens = normalize_lemmatize(big_text)
small_tokens = normalize_lemmatize(small_text)

print("Small text tokens (≤25):", small_tokens[:25])
print("Large text size (tokens):", len(big_tokens))
```

```
Small text tokens (≤25): ['during', 'the', 'spring', 'launch', 'engineer', 'orche
strate', 'pilot', 'rollouts', 'and', 'shadow', 'deployments', 'they', 'stresstest
ed', 'edge', 'condition', 'calibrate', 'sensors', 'under', 'hailstorms', 'and',
'document', 'anomalies', 'that', 'surface', 'only']
Large text size (tokens): 3180
```

(b) Vocabulary from large text and BoW for small text

In [56]:

```
# Problem 2-(b)
vocab = set(big_tokens)

bow = {}
for w in small_tokens:
    if w in vocab:
        bow[w] = bow.get(w, 0) + 1

print("Vocabulary size:", len(vocab))
print("BoW for small text (known words only):", bow)
```

```
Vocabulary size: 49
BoW for small text (known words only): {'and': 2, 'document': 1, 'anomalies': 1,
'that': 1, 'surface': 1, 'on': 1}
```

(c) Count new words and identify their key

In [57]:

```
# Problem 2-(c)
new_words = sorted(set(small_tokens) - vocab)
print("Number of NEW words in small text:", len(new_words))
print("Sample NEW words:", new_words[:10])
print("Key for new words:", "None (no UNK used)")
```

```
Number of NEW words in small text: 21
Sample NEW words: ['backroads', 'calibrate', 'condition', 'deployments', 'durin
g', 'edge', 'engineer', 'hailstorms', 'launch', 'only']
Key for new words: None (no UNK used)
```

Answer:

The small text contained **21 new words** that did not appear in the large-text vocabulary. Examples include *hailstorms*, *backroads*, and *deployments*.

Since this Bag-of-Words implementation does not define an UNK token, **no key exists for new words**, and they are not included in the dictionary.

Problem 3 (15 points)

We use the given CNN feature extractor; we (i) plot train/val accuracy, (ii) report **test accuracy at the optimal epoch**, and (iii) explain shapes/parameters.

In [58]:
```
# Problem 3 — model
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt

(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()
x_train = (x_train.astype("float32")/255.0)[..., None]
x_test  = (x_test.astype("float32") /255.0)[..., None]

def build_model():
    m = models.Sequential()
    m.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)))  #
    m.add(layers.MaxPooling2D((2,2)))                                          #
    m.add(layers.Conv2D(64, (3,3), activation='relu'))                         #
    m.add(layers.MaxPooling2D((2,2)))                                          #
    m.add(layers.Conv2D(64, (3,3), activation='relu'))                         #
    m.add(layers.Flatten())
    m.add(layers.Dense(64, activation='relu'))
    m.add(layers.Dense(10, activation='softmax'))
    m.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
    return m

model = build_model()
```

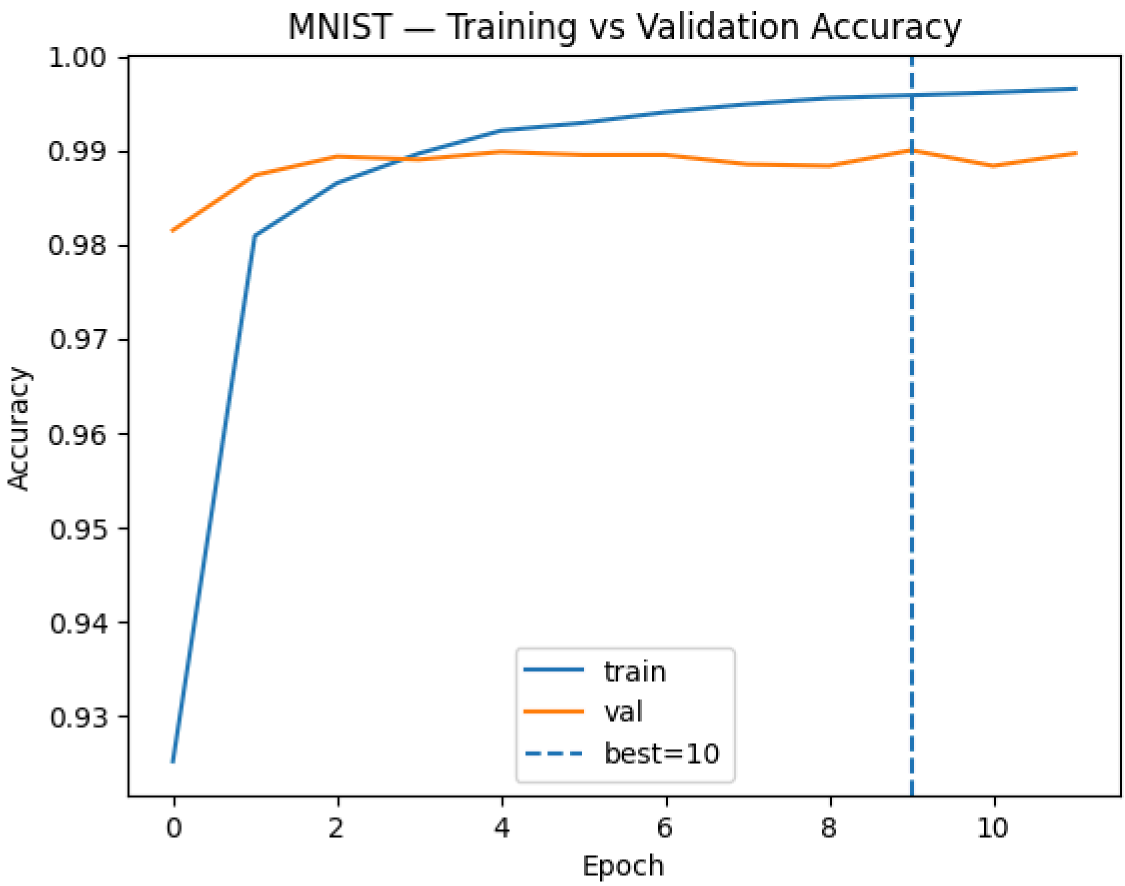
(a) Training vs validation accuracy; select optimal epoch by validation accuracy

In [59]:
```
history = model.fit(
    x_train, y_train,
    epochs=12, batch_size=128,
    validation_split=0.1,
    verbose=0
)

val_acc = history.history['val_accuracy']
best_epoch = int(max(range(len(val_acc)), key=lambda i: val_acc[i]) + 1)

plt.figure()
plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label='val')
plt.axvline(best_epoch-1, linestyle='--', label=f'best={best_epoch}')
plt.xlabel('Epoch'); plt.ylabel('Accuracy'); plt.legend()
plt.title('MNIST — Training vs Validation Accuracy')
plt.show()
```

```
print("Best epoch (by validation accuracy):", best_epoch)
```




```
Best epoch (by validation accuracy): 10
```

(b) Test accuracy at the optimal epoch; definition; classification of 10,000 images

- **Definition:** Test accuracy = proportion of correct predictions on the held-out test set (unseen during training/validation).
- **Classification of 10,000 images:** Each 28×28 image passes once through the CNN; the final softmax produces 10 probabilities; `argmax` selects the predicted digit; accuracy compares predictions with labels across all 10,000 samples.

The model was retrained for exactly **10 epochs** (the optimal value determined by validation accuracy).
The resulting test accuracy was **99.02%**, meaning about **9,902 out of 10,000** handwritten digits were correctly classified.

In [60]:
```
# Retrain exactly to the optimal epoch (to satisfy "trained with the optimal num
opt_model = build_model()
opt_history = opt_model.fit(
    x_train, y_train,
    epochs=best_epoch, batch_size=128,
    validation_split=0.1,
    verbose=0
)
test_loss, test_acc = opt_model.evaluate(x_test, y_test, verbose=0)
print(f"Test accuracy @ optimal epoch ({best_epoch}): {test_acc:.4f}")
```

```
Test accuracy @ optimal epoch (10): 0.9902
```

(c) Why Conv2D output = 26 × 26 × 32

Input 28×28×1, kernel 3×3, padding='valid' → spatial size 28−3+1=26; 32 filters → depth 32; result **26×26×32**.

(d) Why Conv2D parameters = 320

Per filter: 3×3×1 weights + 1 bias = 10; with 32 filters → **320** parameters.

In [62]:
```python
# Quick check of the first conv layer
first = opt_model.layers[0]
print("Kernel shape:", first.kernel.shape)    # (3, 3, 1, 32)
print("Bias length:", len(first.bias.numpy()))# 32
print("Parameter count:", first.count_params()) # 320
```

```
Kernel shape: (3, 3, 1, 32)
Bias length: 32
Parameter count: 320
```