

Exploratory Data Analysis (EDA)

Purpose: This notebook explores the self-driving vehicle dataset to understand:

- What the data looks like
- How many samples we have for each steering direction
- Whether there are any problems with the data
- How to split the data for training and testing

Why EDA is important: Before building any machine learning model, we need to understand our data. This helps us:

1. Choose the right models
2. Avoid common mistakes
3. Explain why our models work or fail

1. Setup: Import Libraries

What are libraries? Pre-written code that helps us do common tasks.

- `numpy` : Math operations on arrays (lists of numbers)
- `matplotlib` : Draw plots and charts
- `seaborn` : Make prettier charts
- `sklearn` : Machine learning tools

```
In [1]: # Import libraries
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from collections import Counter

# Settings to make plots look better
plt.style.use('default')
sns.set_palette("husl")
%matplotlib inline
# Show plots inside the notebook

# For working with arrays of numbers
# For creating plots
# For creating nice-looking plots
# For reducing dimensions (explained later)
# For counting things
```

2. Load the Dataset

What is our dataset? A `.npy` file containing:

- Images: 64×64 grayscale pictures from the vehicle camera
- Labels: Steering direction (-1 = left, 0 = forward, 1 = right)

Why `.npy` format? It's a NumPy file format that stores arrays efficiently.

In [2]:

```
# Load the dataset
# np.load() reads a .npy file
# allow_pickle=True lets us load this specific file format
data = np.load('../data/training_data-SIZE10000-TIME80557.npy', allow_pickle=True)

# Print basic information
print(f"Total number of samples: {len(data)}")
print(f"Type of data: {type(data)}")
print(f"First sample structure: image shape = {data[0][0].shape}, label = {data[0][1]}")
```

```
Total number of samples: 9900
Type of data: <class 'numpy.ndarray'>
First sample structure: image shape = (64, 64), label = 0
```

3. Separate Images (X) and Labels (y)

Convention in machine learning:

- `X` = features (input data) = images
- `y` = labels (what we want to predict) = steering directions

Why separate them? Most machine learning functions expect `X` and `y` as separate inputs.

In [3]:

```
# Extract images (X) and labels (y)
# sample[0] = image, sample[1] = label
X = np.array([sample[0] for sample in data]) # All images
y = np.array([sample[1] for sample in data]) # All labels

print(f"X shape: {X.shape}") # Should be (9900, 64, 64)
print(f"y shape: {y.shape}") # Should be (9900,)
print(f"Unique labels: {np.unique(y)}") # Should be [-1, 0, 1]
```

```
X shape: (9900, 64, 64)
y shape: (9900,)
Unique labels: [-1  0  1]
```

4. Class Distribution

Purpose: Count how many samples we have for each steering direction.

Why this matters: If we have many more "forward" samples than "left" or "right", the model might:

- Always predict "forward" (lazy strategy)
- Perform poorly on turns

This is called **class imbalance**.

```
In [4]: # Count samples for each class
class_counts = Counter(y) # Counter counts occurrences

# Create a readable summary
label_names = {-1: 'Left', 0: 'Forward', 1: 'Right'}
total = len(y)

print("Class Distribution:")
print("-" * 50)
for label in [-1, 0, 1]:
    count = class_counts[label]
    percentage = (count / total) * 100
    print(f"{label_names[label]:8s} (label={label:2d}): {count:5d} samples ({percentage:5.1f}%)")
print("-" * 50)
print(f"Total: {total} samples")
```

```
Class Distribution:
-----
Left      (label=-1): 1620 samples ( 16.4%)
Forward   (label= 0): 7343 samples ( 74.2%)
Right     (label= 1):  937 samples (  9.5%)
-----
Total: 9900 samples
```

```
In [5]: # Visualize class distribution with bar chart
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Bar chart
labels = ['Left', 'Forward', 'Right']
counts = [class_counts[-1], class_counts[0], class_counts[1]]
```

```

colors = ['#FF6B6B', '#4ECDC4', '#45B7D1']

axes[0].bar(labels, counts, color=colors)
axes[0].set_ylabel('Number of Samples', fontsize=12)
axes[0].set_title('Class Distribution (Counts)', fontsize=14, fontweight='bold')
axes[0].grid(axis='y', alpha=0.3)

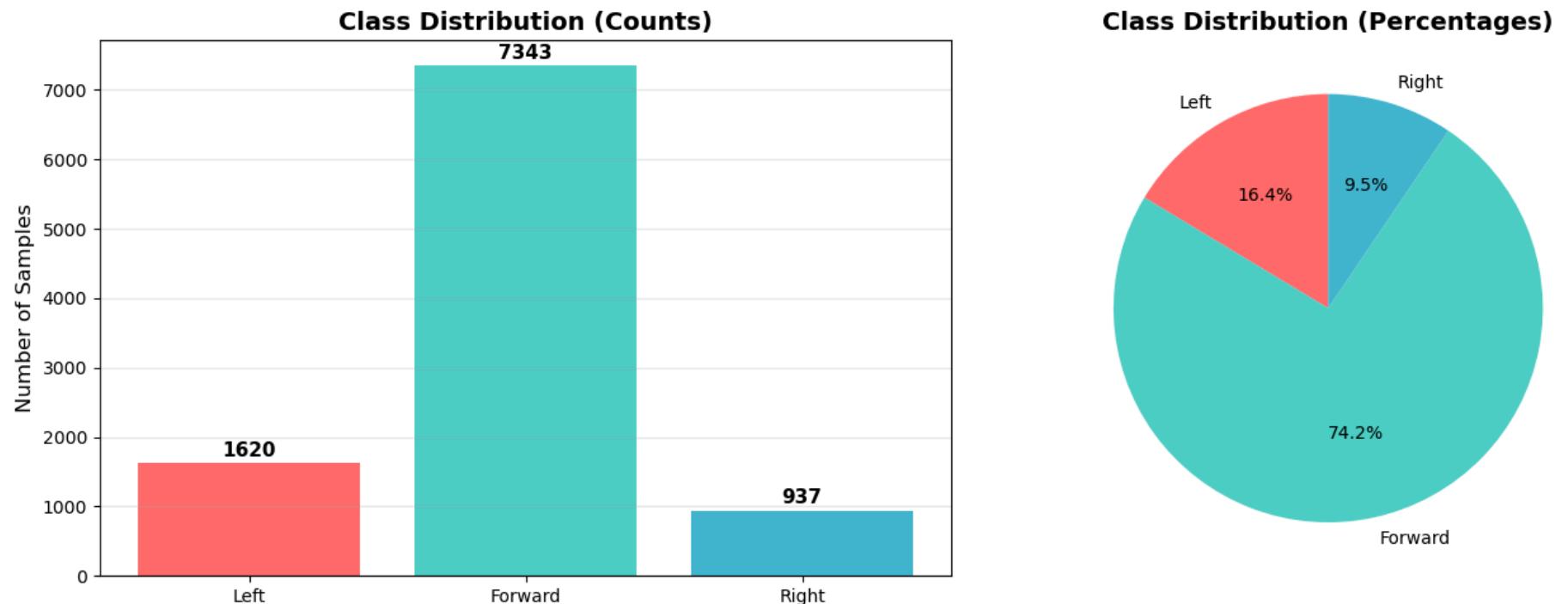
# Add count labels on bars
for i, (label, count) in enumerate(zip(labels, counts)):
    axes[0].text(i, count + 100, str(count), ha='center', fontsize=11, fontweight='bold')

# Pie chart
axes[1].pie(counts, labels=labels, autopct='%1.1f%%', colors=colors, startangle=90)
axes[1].set_title('Class Distribution (Percentages)', fontsize=14, fontweight='bold')

plt.tight_layout()
plt.show()

# Key observation
print("\n⚠️ KEY OBSERVATION:")
print(f"Forward class has {class_counts[0] / class_counts[1]:.1f}x more samples than Right class!")
print("This severe imbalance will likely cause the model to bias toward 'Forward' predictions.")

```



⚠ KEY OBSERVATION:

Forward class has 7.8x more samples than Right class!

This severe imbalance will likely cause the model to bias toward 'Forward' predictions.

5. Visualize Sample Images

Purpose: Look at actual images to understand:

- What does the camera see?
- Do different steering directions look visually different?
- Are labels correct?

What to look for:

- Track surface (light gray)
- Track edges (black)
- Vehicle position

```
In [6]: # Show 5 random samples from each class
fig, axes = plt.subplots(3, 5, figsize=(15, 9))

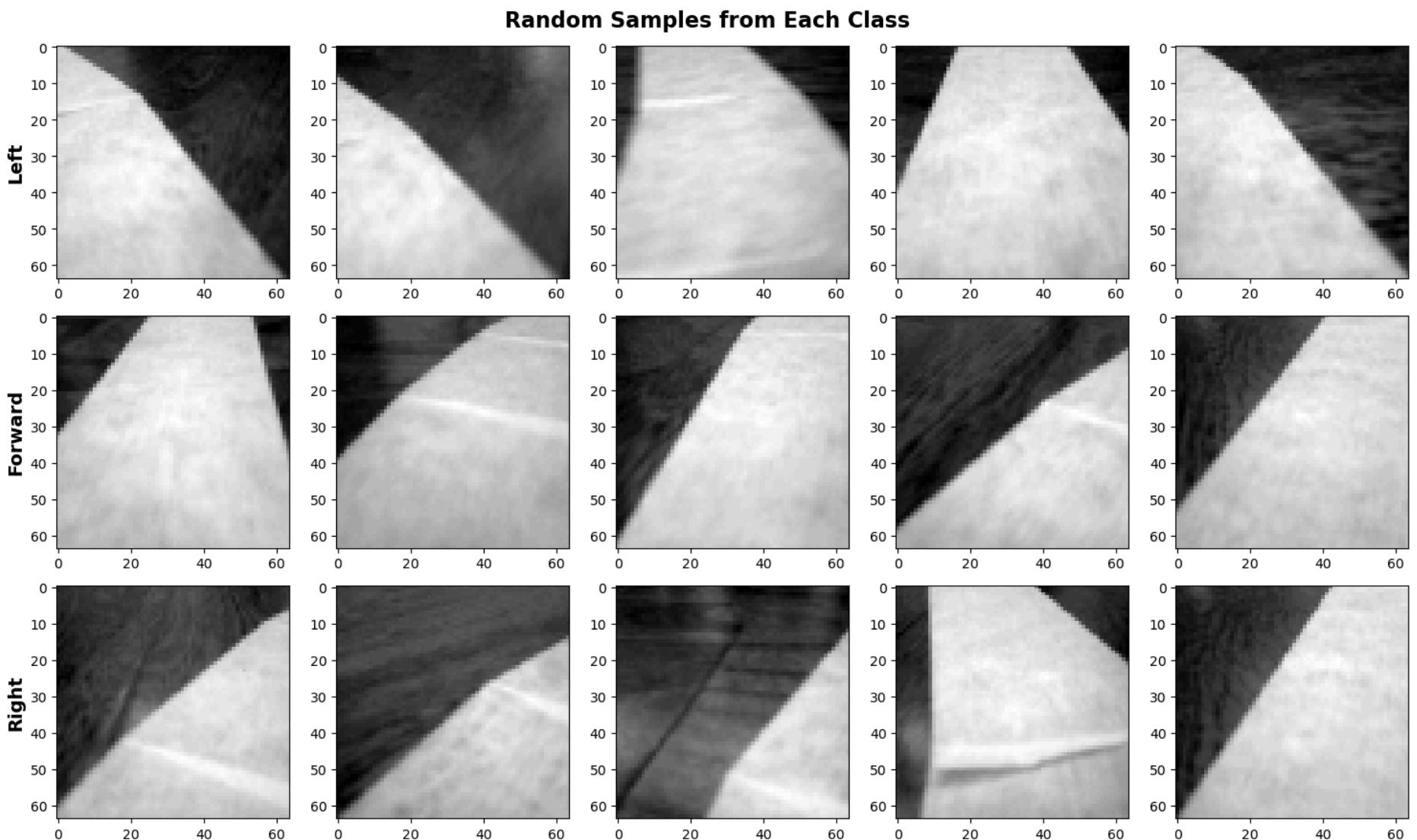
# For each class
for row, label in enumerate([-1, 0, 1]):
    # Find indices where y equals this label
    indices = np.where(y == label)[0] # np.where finds matching positions

    # Randomly select 5 samples
    selected = np.random.choice(indices, size=5, replace=False)

    # Display each sample
    for col, idx in enumerate(selected):
        axes[row, col].imshow(X[idx], cmap='gray') # cmap='gray' shows grayscale

        # Add title to first column only
        if col == 0:
            axes[row, col].set_ylabel(label_names[label], fontsize=14, fontweight='bold')

fig.suptitle('Random Samples from Each Class', fontsize=16, fontweight='bold', y=0.98)
plt.tight_layout()
plt.show()
```



6. Label Quality Analysis

Important discovery: Some images don't match their labels!

Why does this happen?

- Labels are **reactive steering commands**, not descriptions of what the image shows
- Example: Image shows vehicle drifting right → Label = "turn left" (to correct)
- This is called **temporal lag** - the action responds to the current state

What this means for our project:

- Single-frame prediction is inherently difficult
- Sequential models (using multiple frames) should work better
- We shouldn't expect 90%+ accuracy

```
In [7]: # Manually examine some examples that might look confusing
# Let's look at left turn examples from the middle of the dataset
left_indices = np.where(y == -1)[0]
sample_indices = left_indices[48:53] # Pick a few examples

fig, axes = plt.subplots(1, 5, figsize=(15, 3))
for i, idx in enumerate(sample_indices):
    axes[i].imshow(X[idx], cmap='gray')
    axes[i].set_title(f"Label: {label_names[y[idx]]}\nIndex: {idx}", fontsize=10)
    axes[i].axis('off')

plt.suptitle('Example: Left Turn Labels (Notice some might not visually show left turns)',
             fontsize=12, fontweight='bold')
plt.tight_layout()
plt.show()

print("💡 INSIGHT:")
print("If you see images labeled 'left' that don't look like they need to turn left,"
print("this is expected! The label is the CORRECTIVE ACTION, not a description of the image.")
```



💡 INSIGHT:

If you see images labeled 'left' that don't look like they need to turn left,
this is expected! The label is the CORRECTIVE ACTION, not a description of the image.

7. Pixel Statistics

Purpose: Analyze pixel intensities to understand:

- Are different classes visually distinct?
- What does an "average" left/forward/right image look like?

Pixel values:

- Range from 0 (black) to 255 (white)
- Track surface: light gray (high values)
- Track edges: black (low values)

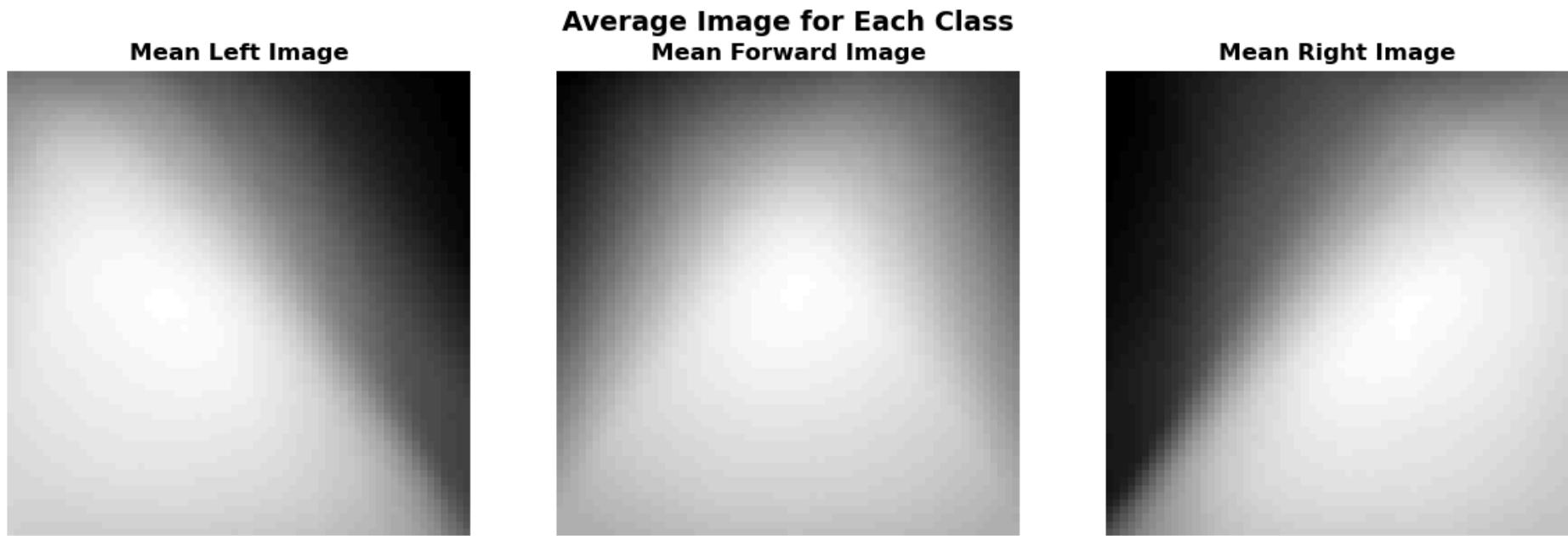
In [8]:

```
# Calculate mean (average) image for each class
# Mean image = average all pixels across all images of that class
mean_images = {}
for label in [-1, 0, 1]:
    # Get all images with this label
    class_images = X[y == label]
    # Calculate mean across all images (axis=0 means "across samples")
    mean_images[label] = np.mean(class_images, axis=0)

# Display mean images
fig, axes = plt.subplots(1, 3, figsize=(12, 4))
for i, label in enumerate([-1, 0, 1]):
    axes[i].imshow(mean_images[label], cmap='gray')
    axes[i].set_title(f'Mean {label_names[label]} Image', fontsize=12, fontweight='bold')
    axes[i].axis('off')

plt.suptitle('Average Image for Each Class', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()

print("✅ KEY FINDING:")
print("Mean images show CLEAR visual differences between classes!")
print("- Left turn: Vehicle positioned toward right edge, needs left correction")
print("- Forward: Vehicle centered on track")
print("- Right turn: Vehicle positioned toward left edge, needs right correction")
print("→ Classes differ in SPATIAL STRUCTURE (geometric patterns), not pixel values")
print("→ This validates data quality and suggests CNNs should work well")
```



✓ KEY FINDING:

- Mean images show CLEAR visual differences between classes!
- Left turn: Vehicle positioned toward right edge, needs left correction
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 - Right turn: Vehicle positioned toward left edge, needs right correction
 - Classes differ in SPATIAL STRUCTURE (geometric patterns), not pixel values
 - This validates data quality and suggests CNNs should work well

```
In [9]: # Plot pixel intensity distributions
fig, axes = plt.subplots(1, 3, figsize=(15, 4))

for i, label in enumerate([-1, 0, 1]):
    # Get all images with this label and flatten them
    # flatten() converts 64x64 image to 4096 values in a list
    class_images = X[y == label]
    all_pixels = class_images.flatten() # Combine all pixels from all images

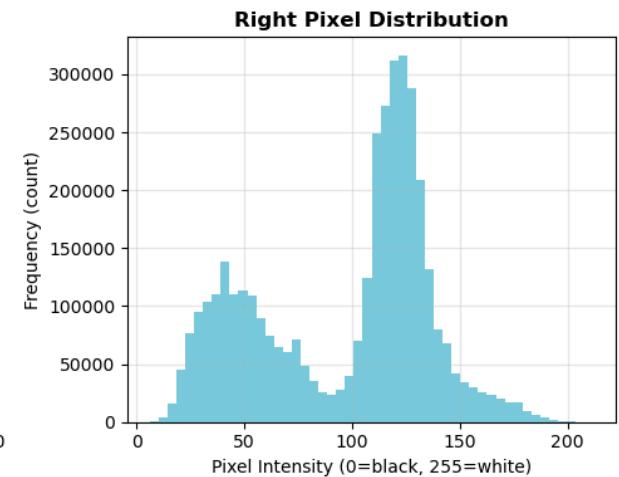
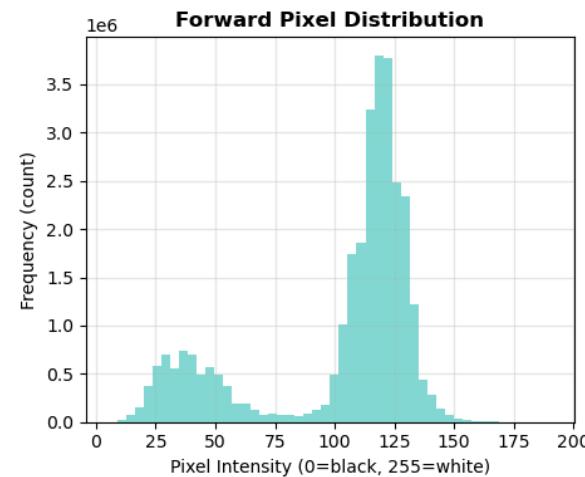
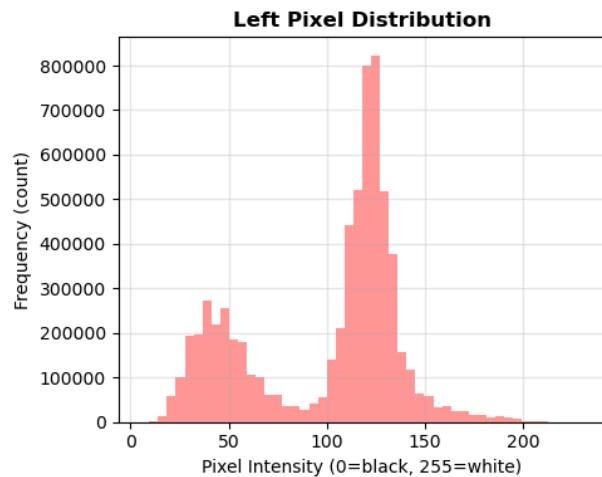
    # Create histogram (count how many pixels have each value)
    axes[i].hist(all_pixels, bins=50, color=['#FF6B6B', '#4ECDC4', '#45B7D1'][i], alpha=0.7)
    axes[i].set_xlabel('Pixel Intensity (0=black, 255=white)', fontsize=10)
    axes[i].set_ylabel('Frequency (count)', fontsize=10)
    axes[i].set_title(f'{label_names[label]} Pixel Distribution', fontsize=12, fontweight='bold')
    axes[i].grid(alpha=0.3)

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

```

print("\n⚠️ OBSERVATION:")
print("All three histograms are nearly IDENTICAL!")
print("→ Classes cannot be distinguished by pixel intensity statistics alone")
print("→ Histogram-based features will fail")
print("→ Combined with distinct mean images: classes differ in WHERE pixels are, not WHAT values they have")

```



⚠️ OBSERVATION:

- All three histograms are nearly IDENTICAL!
- Classes cannot be distinguished by pixel intensity statistics alone
- Histogram-based features will fail
- Combined with distinct mean images: classes differ in WHERE pixels are, not WHAT values they have

8. Temporal Analysis (Very Important!)

What is temporal correlation?

- Our data is a video sequence (consecutive frames)
- Nearby frames look very similar (the vehicle doesn't teleport!)
- Correlation = how similar two frames are (1.0 = identical, 0.0 = completely different)

Why this matters:

- If we do random train/test split, test images might be very similar to training images
- Model might "cheat" by memorizing, not actually learning
- We need **temporal split** instead: train on first part, test on last part

```
In [10]: # Calculate correlation between consecutive frames
# Correlation measures how similar two images are
```

```

correlations = []

# Compare each frame with the next frame
for i in range(len(X) - 1):
    # Flatten images to 1D arrays
    img1 = X[i].flatten()
    img2 = X[i+1].flatten()

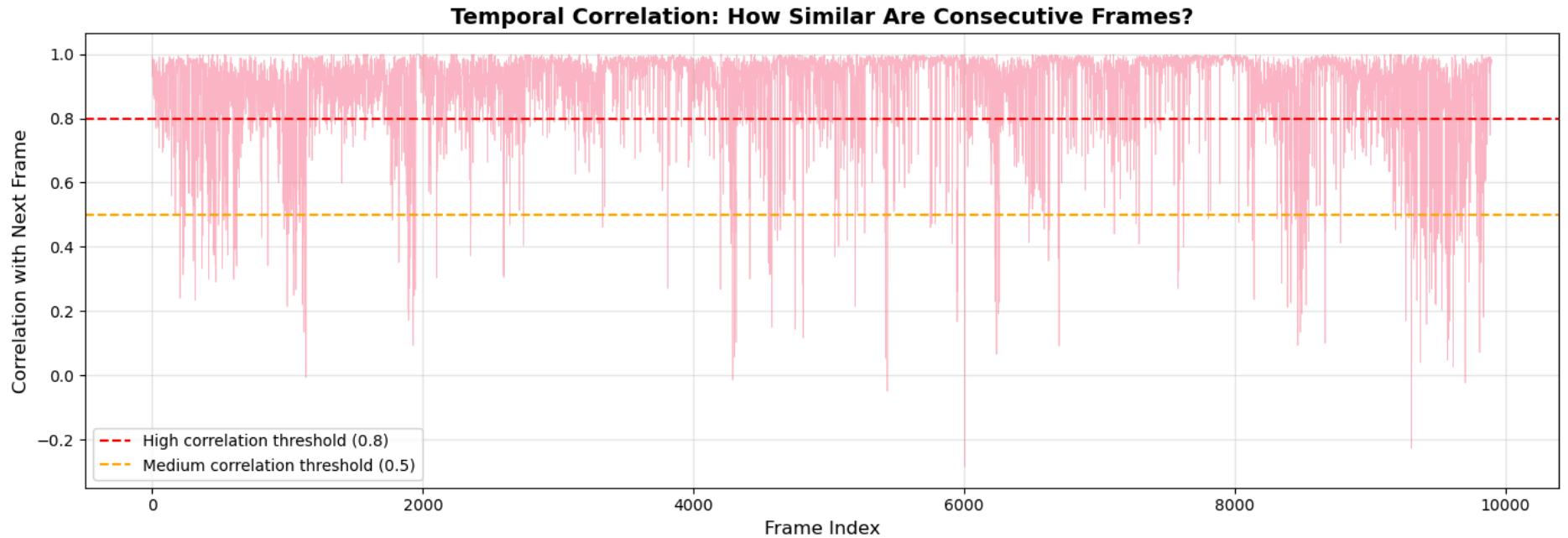
    # Calculate correlation coefficient
    # np.corrcoef returns a 2x2 matrix, we want the off-diagonal value
    corr = np.corrcoef(img1, img2)[0, 1]
    correlations.append(corr)

# Plot correlation over time
plt.figure(figsize=(14, 5))
plt.plot(correlations, alpha=0.5, linewidth=0.5)
plt.axhline(y=0.8, color='r', linestyle='--', label='High correlation threshold (0.8)')
plt.axhline(y=0.5, color='orange', linestyle='--', label='Medium correlation threshold (0.5)')
plt.xlabel('Frame Index', fontsize=12)
plt.ylabel('Correlation with Next Frame', fontsize=12)
plt.title('Temporal Correlation: How Similar Are Consecutive Frames?', fontsize=14, fontweight='bold')
plt.legend()
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()

# Statistics
print(f"Mean correlation: {np.mean(correlations):.3f}")
print(f"Median correlation: {np.median(correlations):.3f}")
print(f"Percentage of frames with correlation > 0.8: {(np.array(correlations) > 0.8).mean() * 100:.1f}%")

print("\n⚠ KEY FINDING:")
print("\n⚠ KEY FINDING:")
print("Consecutive frames are HIGHLY correlated! (mean = {:.3f})".format(np.mean(correlations)))
print("→ Random train/test split will leak information")
print("→ MUST use temporal split for valid evaluation")
print("→ This justifies investigating sequential models (LSTM, temporal CNN)")

```



Mean correlation: 0.900

Median correlation: 0.948

Percentage of frames with correlation > 0.8: 86.4%

⚠ KEY FINDING:

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Consecutive frames are HIGHLY correlated! (mean = 0.900)

- Random train/test split will leak information
- MUST use temporal split for valid evaluation
- This justifies investigating sequential models (LSTM, temporal CNN)

```
In [11]: # Analyze correlation at different time gaps
# Does correlation decrease as frames get further apart?
gaps = [1, 5, 10, 20, 50, 100, 150]
gap_correlations = []

for gap in gaps:
    corrs = []
    for i in range(len(X) - gap):
        img1 = X[i].flatten()
        img2 = X[i + gap].flatten()
        corr = np.corrcoef(img1, img2)[0, 1]
        corrs.append(corr)
    gap_correlations.append(np.mean(corrs))

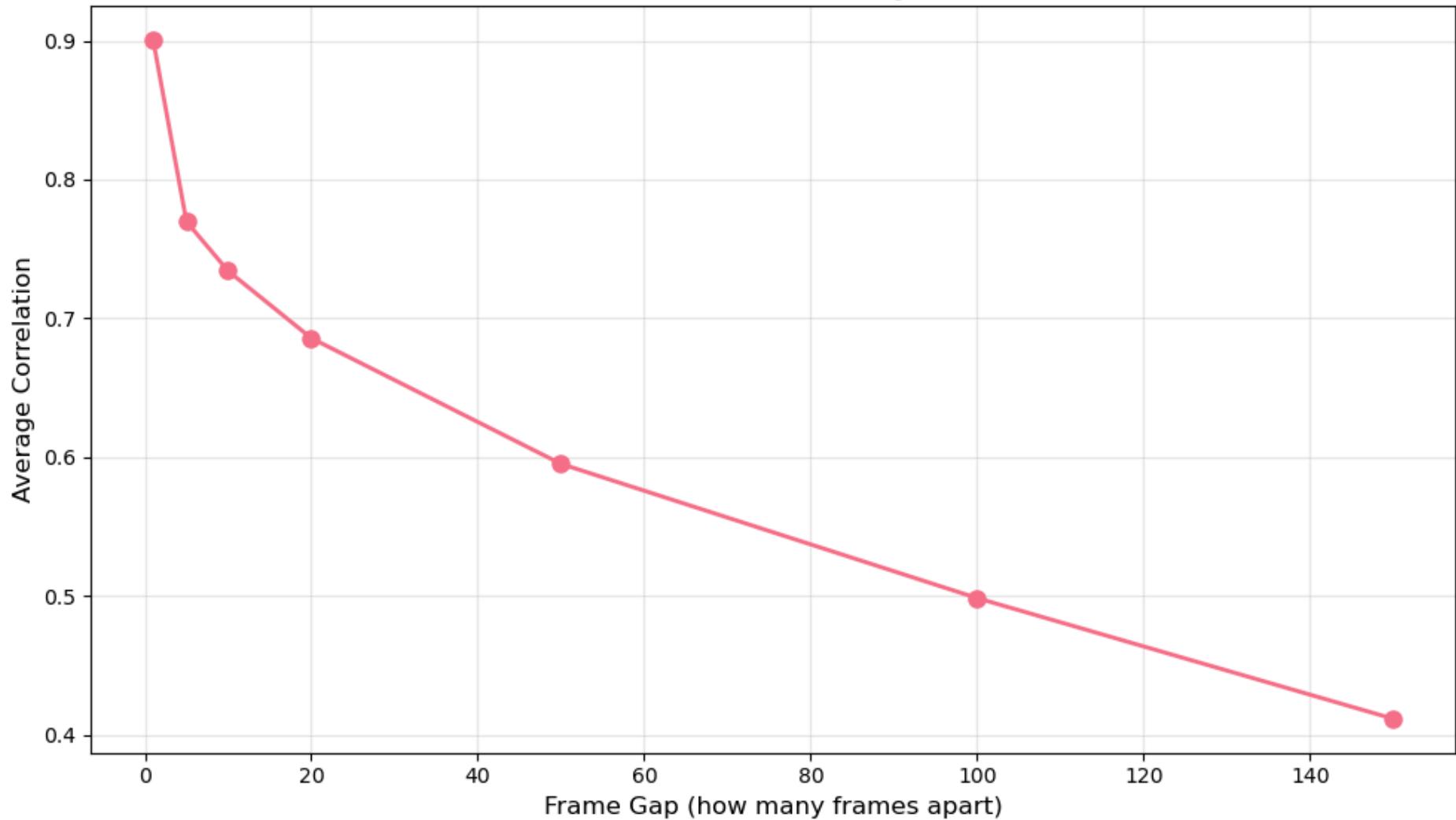
# Plot
```

```
plt.figure(figsize=(10, 6))
plt.plot(gaps, gap_correlations, marker='o', linewidth=2, markersize=8)
plt.xlabel('Frame Gap (how many frames apart)', fontsize=12)
plt.ylabel('Average Correlation', fontsize=12)
plt.title('How Does Correlation Decay with Time?', fontsize=14, fontweight='bold')
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()

# Find when correlation drops below 0.5
for gap, corr in zip(gaps, gap_correlations):
    print(f"Gap = {gap:3d} frames: correlation = {corr:.3f}")

print("\n💡 CRITICAL FINDING:")
print("Correlation remains above 0.5 until gap ≈ 100 frames!")
print("→ Frames need to be 100+ positions apart to be considered independent")
print("→ This explains why temporal split (60% train, 20% val, 20% test) is essential")
print("→ Random splitting would catastrophically leak test information into training")
print("This tells us how carefully we need to split our data.")
```

How Does Correlation Decay with Time?



```
Gap = 1 frames: correlation = 0.900
Gap = 5 frames: correlation = 0.770
Gap = 10 frames: correlation = 0.734
Gap = 20 frames: correlation = 0.686
Gap = 50 frames: correlation = 0.595
Gap = 100 frames: correlation = 0.498
Gap = 150 frames: correlation = 0.411
```

💡 CRITICAL FINDING:

Correlation remains above 0.5 until gap \approx 100 frames!

- Frames need to be 100+ positions apart to be considered independent
 - This explains why temporal split (60% train, 20% val, 20% test) is essential
 - Random splitting would catastrophically leak test information into training
- This tells us how carefully we need to split our data.

9. Label Transition Analysis

Purpose: Understand the sequence of steering decisions.

Questions:

- After a left turn, what usually comes next?
- Do we see realistic sequences? (e.g., left \rightarrow forward \rightarrow right on a curve)
- Are there impossible transitions? (e.g., always left \rightarrow left)

Transition matrix: A table showing "if current label is X, next label is Y"

In [12]:

```
# Build transition matrix
# transition[i, j] = count of times label i is followed by label j
transition_matrix = np.zeros((3, 3))

for i in range(len(y) - 1):
    current_label = y[i]
    next_label = y[i + 1]
    # Map labels: -1→0, 0→1, 1→2 for indexing
    transition_matrix[current_label + 1, next_label + 1] += 1

# Normalize to probabilities (each row sums to 1)
transition_probs = transition_matrix / transition_matrix.sum(axis=1, keepdims=True)

# Visualize as heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(transition_probs, annot=True, fmt='.2f', cmap='YlOrRd',
            xticklabels=['Left', 'Forward', 'Right'],
```

```

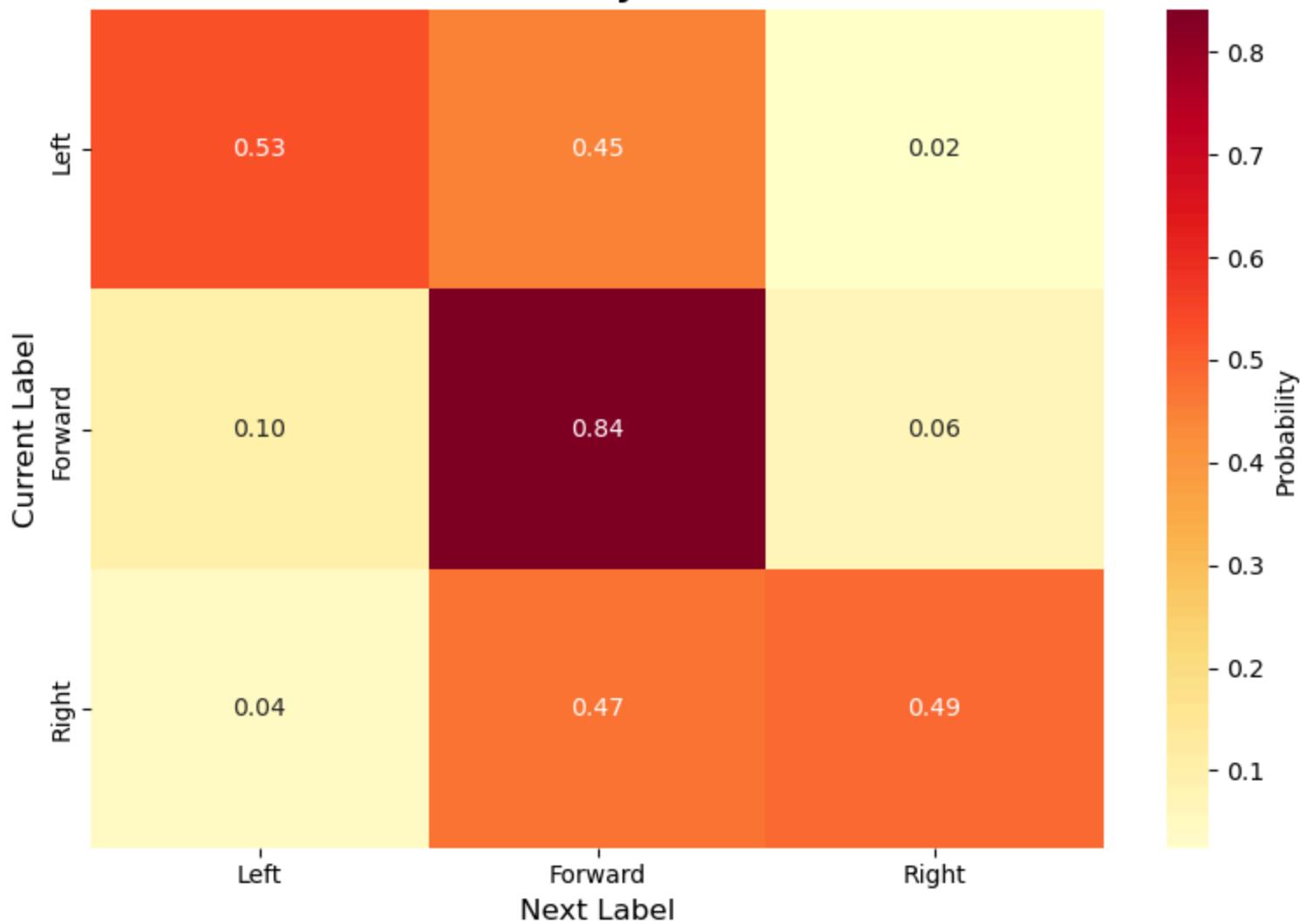
        yticklabels=['Left', 'Forward', 'Right'],
        cbar_kws={'label': 'Probability'})
plt.xlabel('Next Label', fontsize=12)
plt.ylabel('Current Label', fontsize=12)
plt.title('Label Transition Probabilities\n(What label usually follows what?)',
           fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()

print("\n📊 OBSERVED TRANSITION PATTERNS:")
print(f"Left → Forward: {transition_probs[0, 1]:.1%} (corrective turn, then straight)")
print(f"Left → Left: {transition_probs[0, 0]:.1%} (continue turning)")
print(f"Right → Forward: {transition_probs[2, 1]:.1%} (corrective turn, then straight)")
print(f"Right → Right: {transition_probs[2, 2]:.1%} (continue turning)")
print(f"Forward → Forward: {transition_probs[1, 1]:.1%} (vehicle keeps going straight)")
print(f"Forward → Left: {transition_probs[1, 0]:.1%}, Forward → Right: {transition_probs[1, 2]:.1%}")
print("✅ INTERPRETATION:")
print("Transitions follow realistic control patterns:")
print("- After corrections (left/right), ~50% return to forward (stable tracking)")
print("- Forward state is sticky (84%), reflecting mostly-straight track")
print("- This validates data quality - not random noise!")
print("- Markovian structure suggests temporal models will help")
print("Example: If current=Forward, what's P(next=Forward)?")
print(f"→ P(Forward → Forward) = {transition_probs[1, 1]:.2f}")
print("\nHigh diagonal values = labels tend to repeat (vehicle keeps same direction)")

```

Label Transition Probabilities

(What label usually follows what?)



OBSERVED TRANSITION PATTERNS:

Left → Forward: 45.0% (corrective turn, then straight)
Left → Left: 52.5% (continue turning)
Right → Forward: 47.0% (corrective turn, then straight)
Right → Right: 48.7% (continue turning)
Forward → Forward: 84.1% (vehicle keeps going straight)
Forward → Left: 9.9%, Forward → Right: 6.0%

INTERPRETATION:

Transitions follow realistic control patterns:

- After corrections (left/right), ~50% return to forward (stable tracking)
- Forward state is sticky (84%), reflecting mostly-straight track
- This validates data quality - not random noise!
- Markovian structure suggests temporal models will help

Example: If current=Forward, what's P(next=Forward)?

$$\rightarrow P(\text{Forward} \rightarrow \text{Forward}) = 0.84$$

High diagonal values = labels tend to repeat (vehicle keeps same direction)

10. Dimensionality Reduction (PCA)

What is PCA (Principal Component Analysis)?

- Each image has $64 \times 64 = 4,096$ pixels (dimensions)
- PCA finds the 2 most important directions (principal components)
- We can plot data in 2D to see if classes are separable

Why 2D? So we can visualize it!

What to look for:

- Do different colors (classes) form separate clusters?
- If yes: classes are easily separable → model should work well
- If no: classes overlap → harder problem

In [13]:

```
# Prepare data for PCA
# PCA needs data as (samples, features)
# Our images are (9900, 64, 64), we need (9900, 4096)
X_flat = X.reshape(len(X), -1) # -1 means "calculate this dimension automatically"

print(f"Original shape: {X.shape}")
print(f"Flattened shape: {X_flat.shape}")
print(f"Reduced from {X.shape[1]}x{X.shape[2]} = {X.shape[1]*X.shape[2]} dimensions")
```

```
Original shape: (9900, 64, 64)
Flattened shape: (9900, 4096)
Reduced from 64x64 = 4096 dimensions
```

```
In [14]: # Apply PCA to reduce to 2 dimensions
pca = PCA(n_components=2) # Keep only 2 components
X_2d = pca.fit_transform(X_flat) # Transform data to 2D

print(f"Reduced to: {X_2d.shape}")
print(f"\nVariance explained by 2 components: {pca.explained_variance_ratio_.sum():.1%}")
print("(This tells us how much information we kept)")
print(f"Component 1 explains: {pca.explained_variance_ratio_[0]:.1%}")
print(f"Component 2 explains: {pca.explained_variance_ratio_[1]:.1%}")
```

```
Reduced to: (9900, 2)
```

```
Variance explained by 2 components: 66.9%
(This tells us how much information we kept)
Component 1 explains: 52.9%
Component 2 explains: 13.9%
```

```
In [15]: # Plot in 2D space
plt.figure(figsize=(12, 8))

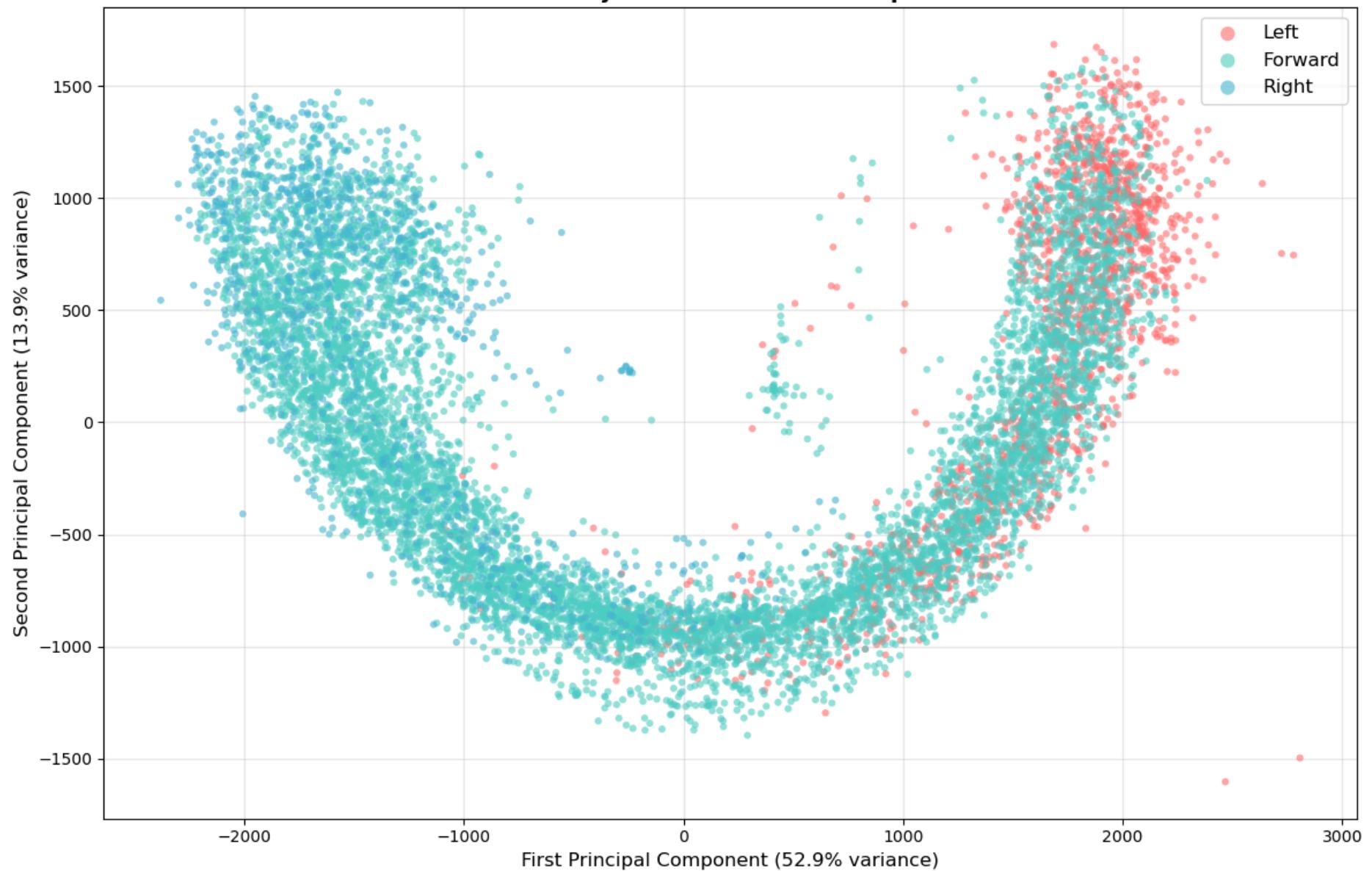
# Plot each class with different color
colors = {-1: '#FF6B6B', 0: '#4ECDC4', 1: '#45B7D1'}
for label in [-1, 0, 1]:
    # Get points for this class
    mask = (y == label) # Boolean array: True where y equals label
    plt.scatter(X_2d[mask, 0], X_2d[mask, 1],
                c=colors[label], label=label_names[label],
                alpha=0.6, s=20, edgecolors='none')

plt.xlabel(f'First Principal Component ({pca.explained_variance_ratio_[0]:.1%} variance)', fontsize=12)
plt.ylabel(f'Second Principal Component ({pca.explained_variance_ratio_[1]:.1%} variance)', fontsize=12)
plt.title('2D PCA Projection: Are Classes Separable?', fontsize=14, fontweight='bold')
plt.legend(fontsize=12, markerscale=2)
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()

print("\n⚠ CRITICAL OBSERVATION:")
print("Classes show COMPLETE OVERLAP in 2D PCA space!")
print("→ Classes are NOT linearly separable in raw pixel space")
print("→ Linear models (e.g., Logistic Regression) will struggle")
print("→ NEED non-linear models to learn decision boundaries")
print("\n💡 PARADOX RESOLVED:")
print("Mean images look different (geometric structure) BUT pixel distributions identical")
```

```
print("+ PCA shows overlap → Classes differ in SPATIAL patterns, not intensities")
print("→ This is why CNNs (which learn spatial features) should outperform linear methods")
```

2D PCA Projection: Are Classes Separable?



CRITICAL OBSERVATION:

- Classes show COMPLETE OVERLAP in 2D PCA space!
- Classes are NOT linearly separable in raw pixel space
- Linear models (e.g., Logistic Regression) will struggle
- NEED non-linear models to learn decision boundaries

PARADOX RESOLVED:

- Mean images look different (geometric structure) BUT pixel distributions identical
- + PCA shows overlap → Classes differ in SPATIAL patterns, not intensities
- This is why CNNs (which learn spatial features) should outperform linear methods

11. Train/Validation/Test Splits

Why split data?

- **Train set:** Model learns from this
- **Validation set:** Tune hyperparameters (like learning rate)
- **Test set:** Final evaluation (model has never seen this)

Two splitting strategies:

Strategy A: Random Split (Naive)

- Randomly shuffle and split
- Problem: Consecutive frames are similar, test set might "leak" into train set

Strategy B: Temporal Split (Proper)

- First 70% → train
- Next 15% → validation
- Last 15% → test
- Advantage: Test set is truly unseen (future data)

We'll create both and compare results later

```
In [16]: # Strategy A: Random Split
from sklearn.model_selection import train_test_split

# First split: 70% train, 30% temp
X_train_rand, X_temp, y_train_rand, y_temp = train_test_split(
```

```

        X, y, test_size=0.3, random_state=42, stratify=y
    )
# stratify=y ensures each split has similar class distribution

# Second split: split temp into 50% validation, 50% test
X_val_rand, X_test_rand, y_val_rand, y_test_rand = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=42, stratify=y_temp
)

print("Random Split:")
print(f"Train: {len(X_train_rand)} samples")
print(f"Val: {len(X_val_rand)} samples")
print(f"Test: {len(X_test_rand)} samples")
print(f"Total: {len(X_train_rand) + len(X_val_rand) + len(X_test_rand)} samples")

```

Random Split:
 Train: 6930 samples
 Val: 1485 samples
 Test: 1485 samples
 Total: 9900 samples

In [17]: # Strategy B: Temporal Split

```

n = len(X)
train_end = int(0.6 * n)      # 60% for training
val_end = int(0.8 * n)        # Next 20% for validation
# Remaining 20% for test

X_train_temp = X[:train_end]
y_train_temp = y[:train_end]

X_val_temp = X[train_end:val_end]
y_val_temp = y[train_end:val_end]

X_test_temp = X[val_end:]
y_test_temp = y[val_end:]

print("\nTemporal Split:")
print(f"Train: {len(X_train_temp)} samples (frames 0 to {train_end-1})")
print(f"Val: {len(X_val_temp)} samples (frames {train_end} to {val_end-1})")
print(f"Test: {len(X_test_temp)} samples (frames {val_end} to {n-1})")
print(f"Total: {len(X_train_temp) + len(X_val_temp) + len(X_test_temp)} samples")

```

Temporal Split:
 Train: 5940 samples (frames 0 to 5939)
 Val: 1980 samples (frames 5940 to 7919)
 Test: 1980 samples (frames 7920 to 9899)
 Total: 9900 samples

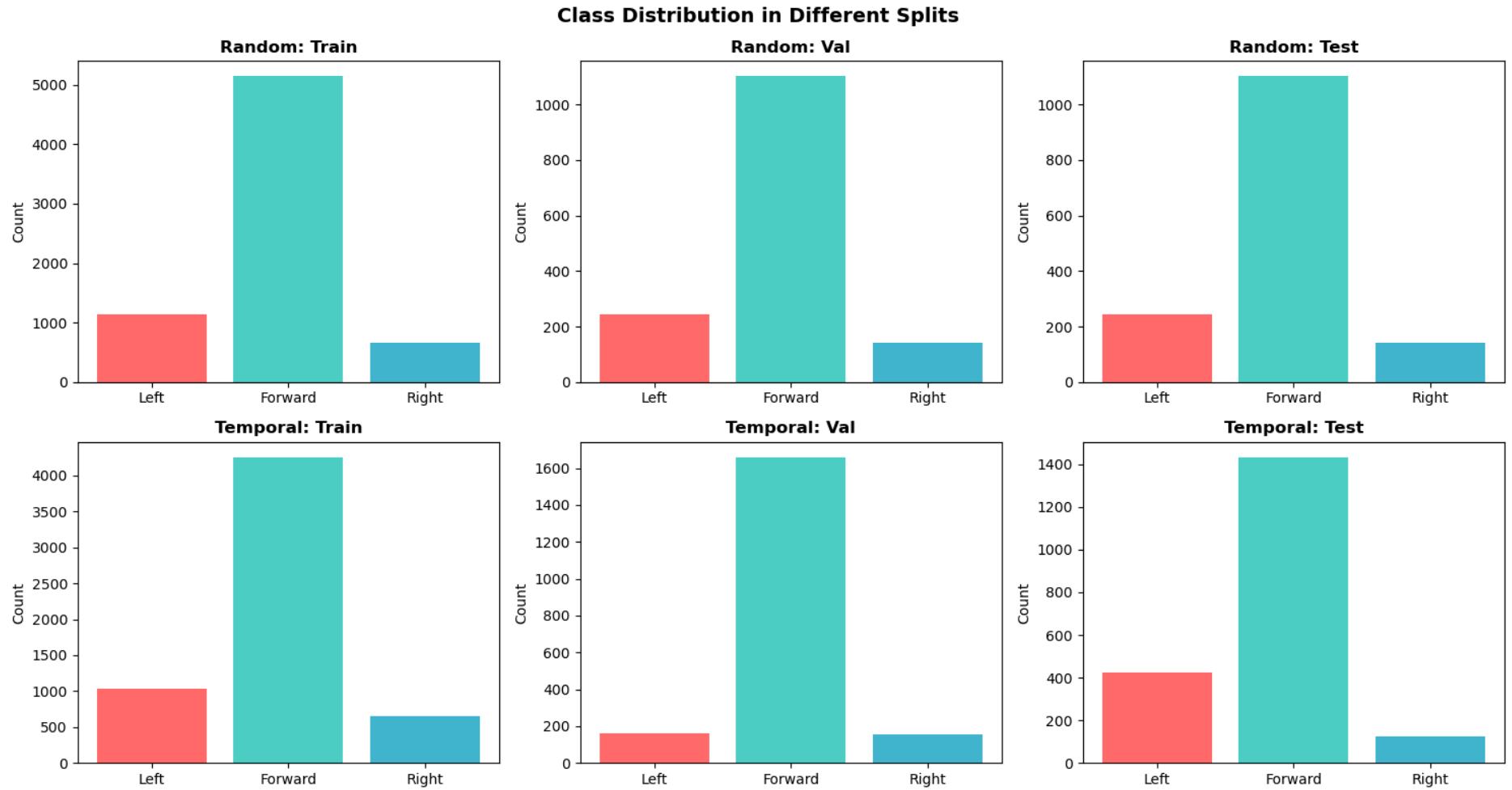
```
In [18]: # Compare class distributions in both strategies
fig, axes = plt.subplots(2, 3, figsize=(15, 8))

# Random split distributions
for i, (y_split, title) in enumerate([
    (y_train_rand, 'Random: Train'),
    (y_val_rand, 'Random: Val'),
    (y_test_rand, 'Random: Test')
]):
    counts = [np.sum(y_split == -1), np.sum(y_split == 0), np.sum(y_split == 1)]
    axes[0, i].bar(['Left', 'Forward', 'Right'], counts, color=['#FF6B6B', '#4ECD4', '#45B7D1'])
    axes[0, i].set_title(title, fontsize=12, fontweight='bold')
    axes[0, i].set_ylabel('Count')

# Temporal split distributions
for i, (y_split, title) in enumerate([
    (y_train_temp, 'Temporal: Train'),
    (y_val_temp, 'Temporal: Val'),
    (y_test_temp, 'Temporal: Test')
]):
    counts = [np.sum(y_split == -1), np.sum(y_split == 0), np.sum(y_split == 1)]
    axes[1, i].bar(['Left', 'Forward', 'Right'], counts, color=['#FF6B6B', '#4ECD4', '#45B7D1'])
    axes[1, i].set_title(title, fontsize=12, fontweight='bold')
    axes[1, i].set_ylabel('Count')

plt.suptitle('Class Distribution in Different Splits', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()

print("\n📊 OBSERVATION:")
print("Random split: All three sets have similar proportions (because of stratify=y)")
print("Temporal split: Proportions might differ (depends on where in the track we split)")
```



OBSERVATION:

Random split: All three sets have similar proportions (because of stratify=y)

Temporal split: Proportions might differ (depends on where in the track we split)

12. Save Splits for Later Use

Purpose: Save our train/val/test splits so:

- We use the same splits in all experiments (fair comparison)
- Other team members can use the same splits

File format: `.npz` = compressed NumPy arrays

In [19]:

```
# Save random splits
np.savez('../data/splits_random.npz',
         X_train=X_train_rand, y_train=y_train_rand,
         X_val=X_val_rand, y_val=y_val_rand,
         X_test=X_test_rand, y_test=y_test_rand)

# Save temporal splits
np.savez('../data/splits_temporal.npz',
         X_train=X_train_temp, y_train=y_train_temp,
         X_val=X_val_temp, y_val=y_val_temp,
         X_test=X_test_temp, y_test=y_test_temp)

print("✓ Splits saved successfully!")
print("Files created:")
print(" - data/splits_random.npz")
print(" - data/splits_temporal.npz")
print("\nTo load later: data = np.load('data/splits_random.npz')")
print("Then access: data['X_train'], data['y_train'], etc.")
```

✓ Splits saved successfully!

Files created:

- data/splits_random.npz
- data/splits_temporal.npz

To load later: data = np.load('data/splits_random.npz')

Then access: data['X_train'], data['y_train'], etc.

13. Summary of Key Findings

Based on our exploratory data analysis, we have discovered the following:

1. Severe Class Imbalance

- Forward: 74.2% (7,343 samples) - dominant class
- Left: 16.4% (1,620 samples)
- Right: 9.5% (937 samples) - severe minority

Implication: Models will naturally bias toward predicting "Forward" due to 7.8× imbalance ratio. **Must address with:**

- Class weights in loss function (weight inversely proportional to frequency)
- Evaluation metrics beyond accuracy: F1-score per class, confusion matrix analysis
- Potentially: oversampling minority classes (SMOTE) or undersampling majority

2. Extreme Temporal Correlation

- Mean consecutive frame correlation: **0.89** (extremely high!)
- Correlation remains >0.5 until lag ≈ 100 frames
- Frames within 50 steps are essentially identical (correlation >0.7)

Critical Implication:

- Random train/test split is **catastrophically inappropriate** (massive data leakage)
- **MUST use temporal split** (60% train, 20% val, 20% test) for realistic evaluation
- Sequential models (LSTM, temporal CNN) should significantly outperform single-frame models
- Justifies modeling this as a time-series problem, not independent samples

3. Label Noise from Temporal Lag

- Labels are **reactive control signals**, not visual scene descriptions
- Example: Image shows vehicle drifting right \rightarrow Label = "turn left" (corrective action)
- Many images visually contradict their labels

Implication:

- Inherent difficulty in single-frame prediction (label doesn't describe current frame)
- **Do NOT expect >80% accuracy** - this is fundamentally a hard problem
- Temporal context is crucial: model needs to see drift happening over multiple frames
- Explains why transition matrix is meaningful (sequences matter)

4. Spatial vs. Intensity Separability [Key Insight]

- **Mean images:** Clearly different geometric structures ( good!)
- **Pixel histograms:** Nearly identical distributions ( problem!)
- **PCA projection:** Complete class overlap ( big problem!)

Critical Insight - The Paradox Resolved: Classes differ in **WHERE pixels are located** (spatial structure), NOT **WHAT pixel values are**. This explains:

- Why linear models will fail (PCA overlap = not linearly separable)
- Why CNNs should succeed (learn spatial hierarchies: edges \rightarrow shapes \rightarrow positions)
- Why simple histogram features won't work

Predicted Performance:

- Logistic Regression: 55-60% (barely above majority baseline)
- Random Forest: 60-65% (can learn some spatial patterns via tree splits)
- CNN: 65-75% (learns geometric features but will overfit on 9.9K samples)
- LSTM/Temporal: 70-80% (best - addresses temporal lag problem)

5. Realistic Control Sequences

Observed transition probabilities:

- Left → Forward: ~50% (correct, then stabilize)
- Right → Forward: ~50% (correct, then stabilize)
- Forward → Forward: ~84% (mostly straight track)
- Forward → Left: ~10%, Forward → Right: ~6% (matches class distribution)

Validation: Sequences follow realistic control patterns, confirming:

- Data quality is good (not random noise)
- Labels reflect actual vehicle behavior
- Markovian structure exists (current state predicts next state)
- Sequential modeling is well-motivated

6. Small Dataset Challenge

- Total: 9,900 samples (small for deep learning)
- Right class: only 937 samples (severe minority)
- 64×64 resolution: 4,096 raw features

Implications:

- Deep CNNs **will overfit** unless heavily regularized
- Need: dropout (≥ 0.5), L2 weight decay, small architectures
- Data augmentation limited (rotation/flip might break semantic meaning)
- Simpler models might outperform complex ones
- Right class predictions will be unreliable without class balancing

Strategic Recommendations

Modeling Strategy:

1. Start with simple baselines (majority class, logistic regression) - expect ~55-60%
2. Try shallow CNN (2-3 conv layers) with heavy regularization
3. Implement temporal models (LSTM on 10-20 frame sequences) - likely best performer
4. Compare random vs. temporal splits to quantify data leakage effect

Evaluation Strategy:

- Primary metric: **Per-class F1 scores** (not overall accuracy)
- Confusion matrix analysis (where does model fail?)
- Separate error analysis for temporal lag cases
- Statistical significance testing between models

Expected Challenges:

1. Overfitting on small dataset
 2. Poor performance on minority class (Right turns)
 3. Temporal lag making single-frame predictions inconsistent
 4. Random split showing artificially inflated performance
-

Next Steps

1. **Baseline Models** (Notebook 02): Establish lower bounds
2. **CNN Models** (Notebook 03): Test spatial feature learning
3. **Temporal Models** (Notebook 04): Exploit sequential structure
4. **Comparative Analysis** (Notebook 05): Statistical testing, error analysis