1 Annotation task details and dataset statistics

In this section we describe the rules developed with our in-house editors for the annotation of match cuts, including examples of match cuts that violate or follow the rules. We show the user interface for annotation, then provide some additional data set statistics.

1.1 Character frame match cutting

1.1.1 Rules

1. Proportions and scales of the characters should be the same.

2. Character poses should be similar.

3. Shots of the same person are okay, as long as there is something different about the shots. E.g. different location, clothes, time of day.

4. Shots should not be too similar.

5. Matches should be between characters, not objects.
1.1.2 Examples

| Example | Match? | Rules violated |
|---------|--------|----------------|
| ![Example 1](image1.png) | No     | 1              |
| ![Example 2](image2.png) | Yes    | None           |
| ![Example 3](image3.png) | No     | 2, 3, 4        |

Examples are from Moonrise Kingdom (2012) [4] and The Matrix (1999) [71].

1.2 Motion Match Cutting

1.2.1 Rules

1. Characters/objects should be moving the same way or the camera motion should be similar. E.g. the camera moves the same direction, or an action-reaction pair in which they move opposite directions.

2. Number of subjects does not have to be the same, as long as the movement, pace and direction are similar.

3. Shots should not be blurry even if the motion is matching.

1.2.2 Examples

| Example | Match? | Rules violated |
|---------|--------|----------------|
| ![Example 4](image4.png) | Yes    | None           |
| ![Example 5](image5.png) | No     | 3              |

Examples in this table are from The Matrix (1999) [71].
1.3 User interface for annotation

We built a custom application for presenting pairs of shots to annotators and collecting labels. Examples are from Moonrise Kingdom (2012) [4].

1.4 Dataset statistics

| Task                              | Frame | Motion | Overall |
|-----------------------------------|-------|--------|---------|
| Annotated pairs                   | 9,985 | 9,320  | 19,305  |
| Positive pairs (majority label)   | 867   | 927    | 1,794   |
| Positive rate                     | 0.087 | 0.099  | 0.093   |
| Pairs with perfect agreement      | 8,373 | 7,027  | 15,400  |
| Perfect agreement rate            | 0.839 | 0.754  | 0.798   |

1.5 Heuristic positive rate

| Heuristic | Pairs selected | Positive pairs | Positive rate |
|-----------|----------------|----------------|---------------|
| $h_1$     | 5,000          | 69             | 0.012         |
| $h_2$     | 5,000          | 808            | 0.161         |
| $h_4$     | 5,000          | 543            | 0.109         |
| $h_5$     | 5,000          | 494            | 0.099         |
1.6 Annotator-level agreement by task

1.7 Annotation candidate pair generation
1.7.1 High-level process
### 1.7.2 Statistics

|                | After shot segmentation | After dedup | Limit to intra-movie | Annotated |
|----------------|-------------------------|-------------|-----------------------|-----------|
| Shots          | 128,202                 | 74,493      | 74,493                | 12,993    |
| Shot pairs     | 8,217,812,301           | 2,774,566,278 | 34,554,612          | 19,305    |
# 2 Title set and shot statistics for the released dataset

## 2.1 Titles

| IMDb ID   | Title                                           | Country           |
|----------|-------------------------------------------------|-------------------|
| tt0050706| Mon Oncle (1958)                                | France            |
| tt0059592| Pierrot le Fou (1965)                            | France            |
| tt0061722| The Graduate (1967)                              | USA               |
| tt0061781| The Firemen's Ball (1967)                         | Czechoslovakia    |
| tt0066921| A Clockwork Orange (1971)                         | UK                |
| tt0070245| Hiroshima Death Match (1973)                      | Japan             |
| tt0070246| Battles Without Honor and Humanity (1973)        | Japan             |
| tt0071315| Chinatown (1974)                                 | USA               |
| tt0079182| Vengeance Is Mine (1979)                          | Japan             |
| tt0080610| The Last Metro (1980)                             | France            |
| tt0081505| The Shining (1980)                                | UK                |
| tt0090257| My Sweet Little Village (1985)                    | Czechoslovakia    |
| tt0092099| Top Gun (1986)                                   | USA               |
| tt0092603| Babette’s Feast (1987)                            | Denmark           |
| tt0095250| The Big Blue (1988)                               | France            |
| tt0095765| Cinema Paradiso (1988)                            | Italy             |
| tt0099685| Goodfellas (1990)                                | USA               |
| tt0101700| Delicatessen (1991)                              | France            |
| tt0106332| Farewell My Concubine (1993)                      | China             |
| tt0108289| Flirting Scholar (1993)                           | Hong Kong         |
| tt0108656| Crime Story (1993)                                | Hong Kong         |
| tt0110201| Hail the Judge (1994)                             | Hong Kong         |
| tt0111797| Eat Drink Man Woman (1994)                        | Taiwan            |
| tt0112769| La Cérémonie (1995)                               | France            |
| tt0114369| Se7en (1995)                                     | USA               |
| tt0118749| Boogie Nights (1997)                              | USA               |
| tt0118799| Life Is Beautiful (1997)                          | Italy             |
| tt0118845| Happy Together (1997)                             | Hong Kong         |
| tt0133093| The Matrix (1999)                                 | USA               |
| tt0175880| Magnolia (1999)                                  | USA               |
| tt0178868| Ringu (1998)                                     | Japan             |
| tt0190332| Crouching Tiger, Hidden Dragon (2000)             | Taiwan            |
| tt0208092| Snatch (2000)                                    | UK                |
| tt0250494| Legally Blonde (2001)                             | USA               |
| tt0266697| Kill Bill: Vol. 1 (2003)                          | USA               |
| tt0308476| The Cuckoo (2002)                                | Russia            |
| tt0338013| Eternal Sunshine of the Spotless Mind (2004)      | USA               |
| tt0373074| Kung Fu Hustle (2004)                             | Hong Kong         |
| tt0378194| Kill Bill: Vol. 2 (2004)                          | USA               |
| tt0385004| House of Flying Daggers (2004)                    | China             |
| tt0387898| Caché (2005)                                     | France            |
| tt0407887| The Departed (2006)                              | USA               |
| tt0427954| The Protector (2005)                              | Thailand          |
| tt0443706| Zodiac (2007)                                    | USA               |
| tt0457430| Pan’s Labyrinth (2006)                            | Mexico            |
| tt0468565| Tsotsi (2005)                                    | UK                |
| tt0469494| There Will Be Blood (2007)                        | USA               |
| tt0477348| No Country for Old Men (2007)                     | USA               |
| Movie ID  | Title                                                      | Year | Country          |
|----------|------------------------------------------------------------|------|------------------|
| tt0765128 | Oceans                                                    | 2009 | France           |
| tt0780504 | Drive                                                     | 2011 | USA              |
| tt0810819 | The Danish Girl                                           | 2015 | UK               |
| tt0844347 | Midnight Sun                                              | 2006 | Japan            |
| tt0887883 | Burn After Reading                                        | 2008 | USA              |
| tt0913425 | Broken Embraces                                           | 2009 | Spain            |
| tt0947798 | Black Swan                                                | 2010 | USA              |
| tt0993846 | The Wolf of Wall Street                                   | 2013 | USA              |
| tt1063669 | The Wave                                                  | 2008 | Germany          |
| tt1220719 | Ip Man                                                    | 2008 | Hong Kong        |
| tt1238299 | 21 Jump Street                                            | 2012 | USA              |
| tt1259593 | Incendies                                                 | 2010 | Canada           |
| tt1276104 | Looper                                                    | 2012 | USA              |
| tt1386932 | Ip Man 2                                                  | 2010 | Hong Kong        |
| tt1462900 | The Grandmaster                                           | 2013 | Hong Kong        |
| tt1504320 | The King’s Speech                                         | 2010 | UK               |
| tt1533117 | Let the Bullets Fly                                       | 2010 | China            |
| tt1560747 | The Master                                                | 2012 | USA              |
| tt1568346 | The Girl with the Dragon Tattoo                           | 2011 | USA              |
| tt1602620 | Amour                                                     | 2012 | Austria          |
| tt1611840 | Once a Gangster                                           | 2010 | Hong Kong        |
| tt1649443 | [REC] 4: Apocalypse                                       | 2014 | Spain            |
| tt1748122 | Moonrise Kingdom                                          | 2012 | USA              |
| tt1800241 | American Hustle                                           | 2013 | USA              |
| tt1832382 | A Separation                                              | 2011 | Iran             |
| tt1853728 | Django Unchained                                          | 2012 | USA              |
| tt1974419 | The Neon Demon                                            | 2016 | Denmark          |
| tt2059255 | No                                                        | 2012 | Chile            |
| tt207649  | Silenced                                                  | 2011 | South Korea      |
| tt2084970 | The Imitation Game                                        | 2014 | USA              |
| tt2115388 | Love is Not Blind                                         | 2011 | China            |
| tt2258281 | Beyond the Hills                                          | 2012 | Romania          |
| tt2267998 | Gone Girl                                                 | 2014 | USA              |
| tt2488496 | Star Wars: Episode VII - The Force Awakens                | 2015 | USA              |
| tt3421514 | Supercondriaque                                           | 2014 | France           |
| tt3501416 | Assassination                                             | 2015 | South Korea      |
| tt3508840 | The Assassin                                              | 2015 | Taiwan           |
| tt3672840 | Dragon Blade                                              | 2015 | China            |
| tt3700392 | Heidi                                                     | 2015 | Germany          |
| tt3808342 | Son of Saul                                               | 2015 | Hungary          |
| tt4176826 | Look Who’s Back                                           | 2015 | Germany          |
| tt4273292 | Under the Shadow                                          | 2016 | UK               |
| tt4967094 | Our Times                                                 | 2015 | Taiwan           |
| tt5576318 | Who Killed Cock Robin?                                    | 2017 | Taiwan           |
| tt5580036 | I, Tonya                                                  | 2017 | UK               |
| tt5593416 | Peach Girl                                                | 2017 | Japan            |
| tt5827496 | At Cafe 6                                                 | 2016 | Taiwan           |
| tt5866930 | The Adventurers                                           | 2017 | China            |
| tt6157626 | Legend of the Demon Cat                                   | 2017 | China            |
| tt6298600 | The Miracles of the Namiya General Store                  | 2017 | Japan            |
| tt6788942 | Bad Genius                                                | 2017 | Thailand         |
2.2 Genre breakdown

Note that titles can have more than one genre.

2.3 Country breakdown
2.4 Release year

2.5 Shot duration statistics

The duration values are in seconds. Note that these values are computed for the subset of shots that we are releasing (not the entire set of shots in all the titles that we have considered).

| Count  | Mean  | Std   | Min  | 25%  | 50%  | 75%  | Max   |
|--------|-------|-------|------|------|------|------|-------|
| 21,205 | 8.174 | 15.136| 0.240| 2.083| 3.879| 8.091| 384.500|

2.6 Shot duration distribution by genre

Note that these values are computed for the subset of shots that we are releasing (not the entire set of shots in all the titles that we have considered).
2.7 Number of unique shots by title

Note that these values are computed for the subset of shots that we are releasing (not the entire set of shots in all the titles that we have considered).
3 Evaluation

3.1 Average Precision (AP)

For match cutting, we surface a ranked list of pairs to editors. Ideally, the best candidates should be placed at the top of this list. Average Precision (AP) is an information retrieval metric that captures this setup. AP ranges between 0 and 1, where a higher value reflects a higher quality of retrieval.

To demonstrate how AP is calculated in our context, consider the following toy dataset with three labeled pairs (all pairs are from Moonrise Kingdom (2012) [4]):

| Pair     | Match? | ID |
|----------|--------|----|
| ![Sample Image](image1.png) | Yes    | A  |
| ![Sample Image](image2.png) | No     | B  |
| ![Sample Image](image3.png) | Yes    | C  |

AP = 1 is achieved when scores for the positives pairs (i.e. A and C), are higher than the score for the negative pair. For instance, if the scores are 0.9, 0.1, and 0.8 for A, B, and C respectively, then we have $AP = 1$. (In this case, the list above would be reordered as A, C, B before it was presented to the editors.)

AP drops below 1 as the scores cause more negatives to be interleaved with positives. For instance, if the scores are 0.9, 0.8, and 0.7 for A, B, and C respectively, then we have $AP = 0.83$.

We use the implementation provided by scikit-learn [56]. The following Python snippet shows how AP is calculated for these two cases:

```
from sklearn.metrics import average_precision_score as ap

# after sorting by score we compute precision at each depth
# if the instance is positive and then divide by the number of positives
assert ap(y_true=[True, False, True], y_score=[0.9, 0.1, 0.8]) == (1 + 1) / 2
assert ap(y_true=[True, False, True], y_score=[0.9, 0.8, 0.7]) == (1 + 2 / 3) / 2
```

3.2 Baseline

Unlike some metrics such as the Area Under the Receiver Operating Characteristic curve (AUROC), AP is not agnostic to the prevalence of the positive examples (we will call this $p$). In other words, we can expect $AUROC = 0.5$ for random guessing regardless of the value of $p$, but $AP = p$ (in expectation) if scores are randomly generated.

Since match cutting is a novel task and no open source benchmarks exist, we treat the positive prevalence $p$ as our baseline, and expect our system to achieve $AP > p$.

The following Python snippet demonstrates that the expected value of AP is $p$: 

```
from sklearn.metrics import average_precision_score as ap

# after sorting by score we compute precision at each depth
# if the instance is positive and then divide by the number of positives
assert ap(y_true=[True, False, True], y_score=[0.9, 0.1, 0.8]) == (1 + 1) / 2
assert ap(y_true=[True, False, True], y_score=[0.9, 0.8, 0.7]) == (1 + 2 / 3) / 2
```

from sklearn.metrics import average_precision_score as ap

```
# after sorting by score we compute precision at each depth
# if the instance is positive and then divide by the number of positives
assert ap(y_true=[True, False, True], y_score=[0.9, 0.1, 0.8]) == (1 + 1) / 2
assert ap(y_true=[True, False, True], y_score=[0.9, 0.8, 0.7]) == (1 + 2 / 3) / 2
```
import numpy as np
from sklearn.metrics import average_precision_score as ap

def random_ap(n: int, p: float) -> float:
    """
    n is the number of candidates.
    p is the positive prevalence.
    """
    assert 0 < p < 1
    scores = np.random.rand(n)
    pos = int(round(p * n))
    true = [True] * pos + [False] * (n - pos)
    return ap(true, scores)

def ap_mean(n: int, p: float, rounds: int, precision: int = 2) -> None:
    aps = [
        random_ap(n=n, p=p)
        for _ in range(rounds)
    ]
    return round(np.mean(aps), precision)

assert ap_mean(n=10_000, p=0.2, rounds=1_000) == 0.2
assert ap_mean(n=10_000, p=0.8, rounds=1_000) == 0.8

3.3 Heuristics

All heuristics described in section 3.3 produce a score given a pair of shots, which can be used for evaluation as described in the previous section. These scores can be used in the same way that we use the output score of a classification model. The only difference is that unlike learned models that can be trained with different seeds, there’s no similar source of variation for heuristics. Therefore we only report a single value instead of mean and standard deviation.
4 Experiment 2 hyperparameters

For all experiments we used:

- TripletMarginMiner with type_of_triplets="hard"
- training batch size of 256

For character frame we use 128 and 1024 hidden units for the first and second layer respectively, and for motion we use 256 and 1024 hidden units in the first two layers of MLP. For character frame we used 300 epochs and for motion we used 100.

4.1 Tuning ranges of hyperparameters

For both tasks we used the following tuning ranges:

| Hyperparameter | Character frame | Motion |
|----------------|-----------------|--------|
| temperature    | $7.362 \times 10^{-3}$ | $1.3412 \times 10^{-2}$ |
| learning_rate  | $3.147 \times 10^{-3}$ | $4.056 \times 10^{-4}$ |
| weight_decay   | $10^{-4}$        | $4.54 \times 10^{-4}$ |

4.2 Tuned hyperparameters