1. Dataset Details

We present more details about our dataset and annotations in this section.

1.1. Image Tagging

Figure 1 shows the distribution of weather, scene, and time of day attributes in BDD100K. The distribution demonstrates visual diversity of the images and thus provides an opportunity to study visual transfer between different domains.

1.2. Object Detection

Table 1:

|                | Caltech [1] | KITTI [3] | City [6] | Ours |
|----------------|-------------|-----------|----------|------|
| # persons      | 1,273       | 6,336     | 19,654   | 86,047|
| # per image    | 1.4         | 0.8       | 7.0      | 1.2  |

Table 1: Comparisons on number of pedestrians with other datasets. The statistics are based on the training set in each dataset. Our dataset has more examples of pedestrians, but because our dataset contains non-city scenes such as highways, the number of person per image is lower than Cityscapes.

1.3. Lane Marking and Drivable Area

Our choice of annotated lane attributes is based on their influence on driving decisions. The continuity of a lane marking is essential for making a “driving-across” decision, so we labeled it independently as an important attribute. Similarly, the direction of a lane marking is also significant for autonomous driving. For example, if a lane marking is parallel to the passing car, it may serve to guide cars and separate lanes; if it is perpendicular, it can be treated as a sign of deceleration or stop. The distribution of the number of annotations in varied driving scenes are shown in Figure 3a, Figure 3b, and Figure 3c. The detailed evaluation results for the lane marking benchmark are in Table 5.

Drivable area detection is a new task, so we show results of a baseline method on the task here. First, the drivable area detection is converted to 3-way segmentation task (background, directly, and alternatively drivable) by ignoring the region ID. Then, we train DRN-D-22 model [5] on the 70,000 training images. We find that after learning from the large-scale image dataset, the model learns to split the road according to the lanes and extrapolate the drivable area to unmarked space. The mIoU for directly and alternatively drivable areas is 79.4% and 63.3%. However, the same model can achieve much higher accuracy on road segmentation, which indicates that techniques beyond segmentation may be required to solve the drivable area problem.

1.4. GPS Trajectory

Figure 4 shows GPS trajectories of example sequences. Our data presents diverse driving behaviors, like starting, stopping, turning and passing. The data is suitable to train and test imitation learning algorithms on real driving data.

1.5. Semantic Instance Segmentation

Figure 5 shows the distribution of number of instances observed in the segmentation annotations. BDD100K has a good coverage on rare categories (e.g. trailer, train) and large number of instances of common traffic objects such as persons and cars. We also observe long-tail effects on our dataset. There are almost 60 thousand car instances, a few hundred rider and motorcycle instances, and mere dozens of trailer and train instances.

Figure 9 in the main paper shows some segmentation examples produced by DRN-D-38. They also reveal some interesting properties of various domains. Probably because of the infrastructure differences between Germany and the US, the models trained on Cityscapes confuse some big structures in an unreasonable way, such as segmenting the sky as building as shown in the third row of the figure. The model is also confused by the US highway traffic sign. However, the same model trained on our dataset does not
Figure 1: Distribution of images in weather, scene, and day hours categories.

Figure 2: Drivable area prediction by segmentation. The segmentation predicts the drivable area with lanes well, as shown in the top row. Also, we find that the segmentation model learns to interpolate in areas that has no lane markings.

suffer these problems. Also, the model of Cityscapes may over-fit the hood of the data collecting vehicle and produces erroneous segmentation for the lower part of the images.

1.6. Multiple Object Tracking and Segmentation

Table 2 and Table 3 shows the label distributions by categories. Our bounding box tracking annotations cover more than one hundred thousand instances with more than two million bounding boxes, and the segmentation tracking set contains more than six thousand instances with one hundred thousand polygons. We showed in the paper submission, our tracking annotation set is one of the largest out there, in addition to our advantage in multitask and diversity.

2. Model Details

In this section, we present more implementation details for benchmark models.

2.1. Tracking

We use a modified Faster R-CNN [4] architecture for tracking similar with Feichtenhofer et al. [2]. Like Feichtenhofer et al. [2], we use a correlation module and a bounding box propagation (regression) head to estimate the bounding box offset between two frames for short-term association. We also implement an association head based on appearance to learn embeddings for instance re-identification. During training, we sample a pair of frames within the interval of $t = 3$ frames. During inference, we first perform detection for the first frame. For each subsequent frame, we use the propagation head to associate detected bounding boxes with boxes from the previous frame based on overlap. We then use the association head based on appearance to associate the rest with the unmatched boxes in the previous 15 frames using dot product of the embeddings followed by softmax.

### Table 3: Annotations of BDD100K MOTS by category.

|         | Total | person | rider | car | truck | bus | train | motorcycle | bicycle |
|---------|-------|--------|-------|-----|-------|-----|-------|------------|---------|
| Tracks  | 6.3K  | 1.8K   | 31    | 40K | 215   | 93  | 4     | 21         | 76      |
| Masks   | 129K  | 22K    | 894   | 93K | 7.6K  | 4.0K| 117   | 369        | 1.4K    |
| Truncated| 15K   | 833    | 45    | 12K | 13K   | 743 | 8     | 49         | 70      |
| Occluded| 85K   | 13K    | 793   | 61K | 5.7K  | 3.1K| 116   | 292        | 970     |
Figure 3: Distribution of different types of lane markings and drivable areas.

(a) Lane category
(b) Lane direction
(c) Lane continuity
(d) Drivable areas

Figure 4: Trajectories of example driving videos.

Figure 5: Distribution of classes in semantic instance segmentation. It presents a long-tail effect with more than 10 cars and poles per image, but only tens of trains in the whole dataset.

Figure 6: Example annotations for BDD100K MOTS. Frames are down-sampled for visualization.
| Train (30K) | Test  | AP   | AP_{50} | AP_{75} | AP_{S} | AP_{M} | AP_{L} |
|------------|-------|------|---------|---------|--------|--------|--------|
| City       |       | 29.5 | 55.3    | 27.2    | 14.4   | 32.8   | 47.2   |
| Non-City   | City  | 24.9 | 48.6    | 22.1    | 11.7   | 28.1   | 40.7   |
| Random     |       | 28.7 | 54.5    | 25.8    | 13.7   | 31.9   | 47.0   |
| City       |       | 26.5 | 49.3    | 25.5    | 13.5   | 32.1   | 47.0   |
| Non-City   | Non-City | 24.3 | 46.0    | 22.4    | 13.3   | 30.0   | 42.0   |
| Random     |       | 26.6 | 49.8    | 24.4    | 14.4   | 31.8   | 47.4   |
| City       |       | 28.8 | 54.1    | 26.8    | 13.8   | 32.7   | 47.0   |
| Non-City   |       | 24.9 | 48.3    | 22.2    | 11.8   | 28.7   | 41.2   |
| Random     |       | 28.7 | 54.5    | 25.8    | 13.7   | 31.9   | 47.0   |
| City       |       | 26.5 | 49.3    | 25.5    | 13.5   | 32.1   | 47.0   |
| Non-City   |       | 24.3 | 46.0    | 22.4    | 13.3   | 30.0   | 42.0   |
| Random     |       | 26.6 | 49.8    | 24.4    | 14.4   | 31.8   | 47.4   |
| City       |       | 28.8 | 54.1    | 26.8    | 13.8   | 32.7   | 47.0   |
| Non-City   |       | 24.9 | 48.3    | 22.2    | 11.8   | 28.7   | 41.2   |
| Random     |       | 28.7 | 54.5    | 25.8    | 13.7   | 31.9   | 47.0   |
| City       |       | 26.5 | 49.3    | 25.5    | 13.5   | 32.1   | 47.0   |
| Non-City   |       | 24.3 | 46.0    | 22.4    | 13.3   | 30.0   | 42.0   |
| Random     |       | 26.6 | 49.8    | 24.4    | 14.4   | 31.8   | 47.4   |

Table 4: Full evaluation results of the domain discrepancy experiments with object detection.

| Threshold | Training Set | Direction | Continuity | Category | avg. | total avg. |
|-----------|--------------|------------|------------|----------|------|------------|
|           |              | parallel   | vertical   | avg.     |      |            |
|           |              | continuous | dashed avg.|          |      |            |
|           |              | crosswalk  | double white|         |      |            |
|           |              | double yellow|          |        |      |            |
|           |              | road curb  | single white|        |      |            |
|           |              | single yellow|         |        |      |            |
| τ = 1     | Lane 10K     | 28.41      | 28.35      | 28.38   | 28.31| 28.32      |
|           | Lane+Drivable10K | 31.19 | 32.46 | 31.83 | 31.89 | 31.84 | 31.85 |
|           | Lane 20K     | 34.45      | 36.62      | 35.54   | 34.58| 34.61      |
|           | Lane+Drivable20K | 34.45 | 36.32 | 35.38 | 34.51 | 34.32 | 34.33 |
|           | Lane 70K     | 35.7       | 36.92      | 35.74   | 34.62| 34.85      |
|           | Lane+Drivable70K | 34.48 | 36.60 | 35.54 | 34.49 | 34.62 | 34.63 |
| τ = 2     | Lane 10K     | 35.76      | 36.63      | 36.19   | 35.48| 33.91      |
|           | Lane+Drivable10K | 38.79 | 41.26 | 40.03 | 39.28 | 37.01 | 38.14 |
|           | Lane 20K     | 42.24      | 46.03      | 44.23   | 42.32| 42.41      |
|           | Lane+Drivable20K | 42.42 | 45.65 | 44.03 | 42.22 | 42.06 | 42.14 |
|           | Lane 70K     | 42.56      | 46.40      | 44.48   | 42.32| 42.71      |
|           | Lane+Drivable70K | 42.48 | 46.00 | 44.24 | 42.18 | 42.46 | 42.32 |
| τ = 10    | Lane 10K     | 49.35      | 49.22      | 49.29   | 48.32| 47.39      |
|           | Lane+Drivable10K | 54.07 | 53.87 | 53.97 | 52.61 | 52.57 | 52.59 |
|           | Lane 20K     | 56.34      | 58.38      | 57.36   | 54.71| 56.99      |
|           | Lane+Drivable20K | 56.31 | 58.07 | 57.19 | 54.59 | 56.69 | 55.64 |
|           | Lane 70K     | 56.3       | 58.70      | 57.50   | 54.59| 57.16      |
|           | Lane+Drivable70K | 56.41 | 58.29 | 57.35 | 54.53 | 56.98 | 55.76 |

Table 5: Full evaluation results of the individual lane marking task and the joint training of lane marking and the drivable area detection. We report the ODS-F scores with different thresholds τ = 1, 2, 10 pixels of direction, continuity as well as each category.
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