

# evaluating models with W&B

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In this section, we will explore how to evaluate machine learning models using Weights & Biases (W&B). W&B provides a suite of tools that make it easy to track experiments, visualize results, and share findings with collaborators. We will cover the following topics:

1. Setting up W&B for model evaluation
2. Logging evaluation metrics
3. Visualizing results with W&B dashboards
4. Comparing different models and experiments
5. Sharing results with collaborators

## Setting up W&B for model evaluation

To get started with W&B, you need to install the W&B library and set up an

```
account. You can install the library using pip:
```bash
pip install wandb
```d create an account on the W&B website. Once you have an
account, you can initialize W&B in your Python script:
```python
import wandb
wandb.init(project="model-evaluation")
```
```

This will create a new project in your W&B dashboard where you can log evaluation metrics and visualize results.

## Logging evaluation metrics

Once W&B is set up, you can log evaluation metrics during your model evaluation process. For

example, if you are evaluating a classification model, you might want to log metrics such as accuracy, precision, recall, and F1-score. You can log these metrics using the `wandb.log()` function:

```
# Example evaluation metrics
accuracy = 0.95
precision = 0.92
recall = 0.93
f1_score = 0.925
# Log metrics to W&B
```

```
wandb.log({"accuracy": accuracy,
          "precision": precision,
          "recall": recall,
          "f1_score": f1_score})
```

You can log metrics at different stages of your evaluation process, such as after each epoch or after evaluating on a validation set.

## Visualizing results with W&B dashboards

W&B provides powerful visualization tools that allow you to create custom dashboards to visualize your evaluation metrics. You can create line plots, bar charts, and other visualizations to track the performance of your model over time. For example, you can create a line plot to visualize the accuracy of your model over multiple evaluation runs:

```
# Log accuracy over multiple runs
for epoch in range(10):
    accuracy = 0.9 + epoch * 0.01 # Example accuracy value
    wandb.log({"epoch": epoch, "accuracy": accuracy})
```

You can then create a line plot in your W&B dashboard to visualize the accuracy over epochs.

## Comparing different models and experiments

W&B makes it easy to compare different models and experiments. You can create multiple runs within the same project and log evaluation metrics for each run. This allows you to compare the performance of different models side by side. For example, you can log metrics for two different models:

```
# Log metrics for Model A
wandb.init(project="model-evaluation", name="Model_A")
wandb.log({"accuracy": 0.95, "precision": 0.92, "recall": 0.93,
          "f1_score": 0.925})
wandb.finish()
# Log metrics for Model B
wandb.init(project="model-evaluation", name="Model_B")
wandb.log({"accuracy": 0.96, "precision": 0.94, "recall": 0.92,
          "f1_score": 0.93})
wandb.finish()
```

You can then use the W&B dashboard to compare the metrics of Model A and Model B. To create an account on the W&B website. Once you have an account, you can initialize W&B in your Python script:

```
import wandb
wandb.init(project="model-evaluation")
``` This will create a new project in your W&B dashboard where
you can log evaluation metrics and visualize results.
## Sharing results with collaborators
W&B makes it easy to share your evaluation results with
collaborators. You can share your W&B project link with others,
allowing them to view your evaluation metrics and visualizations.
You can also invite collaborators to your W&B project, giving
them access to the project dashboard and the ability to log their
own metrics. To invite collaborators, go to your W&B project
dashboard, click on the "Settings" tab, and then click on "Invite
Collaborators". You can enter the email addresses of your
collaborators to send them an invitation.
By following these steps, you can effectively evaluate your
machine learning models using W&B, track performance metrics,
visualize results, compare different models, and share findings
with your collaborators.
```

### ##W&B with Hugging Face for image classification

In this section, we will explore how to use Weights & Biases (W&B) in conjunction with Hugging Face for evaluating image classification models. Hugging Face provides a wide range of pre-trained models and tools that make it easy to build and evaluate machine learning models. We will cover the following topics:

1. Setting up W&B and Hugging Face
2. Loading a pre-trained image classification model
3. Evaluating the model on a dataset
4. Logging evaluation metrics to W&B
5. Visualizing results with W&B dashboards
6. Sharing results with collaborators

#### ## Setting up W&B and Hugging Face

To get started, you need to install the W&B and Hugging Face libraries. You can

install the libraries using pip:

```
```bash
pip install wandb transformers datasets
```

Next, create an account on the W&B website and set up your Hugging Face account if

you haven't already. Once you have both accounts, you can initialize W&B in your Python script:

```
import wandb
wandb.init(project="image-classification-evaluation")
```

This will create a new project in your W&B dashboard where you can log evaluation metrics and visualize results.

## Loading a pre-trained image classification model

Hugging Face provides a variety of pre-trained image classification models that you can use for evaluation. You can load a pre-trained model using the `transformers` library. For example, you can load a ResNet model as follows:

```
from transformers import AutoModelForImageClassification,
AutoFeatureExtractor

model =
AutoModelForImageClassification.from_pretrained("microsoft/resnet
-50")
feature_extractor =
AutoFeatureExtractor.from_pretrained("microsoft/resnet-50")
```

## Evaluating the model on a dataset

To evaluate the model, you need a dataset. Hugging Face's `datasets` library provides a variety of datasets that you can use. For example, you can load the CIFAR-10