In [ ]:
```
#hide
!pip install -Uqq fastbook
import fastbook
fastbook.setup_book()
```

In [ ]:
```
#hide
from fastbook import *
from fastai.vision.widgets import *
```

[[chapter_production]]

From Model to Production

The six lines of code we saw in <> are just one small part of the process of using deep learning in practice. In this chapter, we're going to use a computer vision example to look at the end-to-end process of creating a deep learning application. More specifically, we're going to build a bear classifier! In the process, we'll discuss the capabilities and constraints of deep learning, explore how to create datasets, look at possible gotchas when using deep learning in practice, and more. Many of the key points will apply equally well to other deep learning problems, such as those in <>. If you work through a problem similar in key respects to our example problems, we expect you to get excellent results with little code, quickly.

Let's start with how you should frame your problem.

The Practice of Deep Learning

We've seen that deep learning can solve a lot of challenging problems quickly and with little code. As a beginner, there's a sweet spot of problems that are similar enough to our example problems that you can very quickly get extremely useful results. However, deep learning isn't magic! The same 6 lines of code won't work for every problem anyone can think of today. Underestimating the constraints and overestimating the capabilities of deep learning may lead to frustratingly poor results, at least until you gain some experience and can solve the problems that arise. Conversely, overestimating the constraints and underestimating the capabilities of deep learning may mean you do not attempt a solvable problem because you talk yourself out of it.

We often talk to people who underestimate both the constraints and the capabilities of deep learning. Both of these can be problems: underestimating the capabilities means that you might not even try things that could be very beneficial, and underestimating the constraints might mean that you fail to consider and react to important issues.

The best thing to do is to keep an open mind. If you remain open to the possibility that deep learning might solve part of your problem with less data or complexity than you expect, then it is possible to design a process where you can find the specific capabilities and constraints related to your particular problem as you work through the process. This doesn't mean making any risky bets — we will show you how you can gradually roll out models so that they don't create significant risks, and can even backtest them prior to putting them in production.

Starting Your Project

So where should you start your deep learning journey? The most important thing is to ensure that you have some project to work on—it is only through working on your own projects that you will get real experience building and using models. When selecting a project, the most important consideration is data availability. Regardless of whether you are doing a project just for your own learning or for practical application in your organization, you want something where you can get started quickly. We have seen many students, researchers, and industry practitioners waste months or years while they attempt to find their perfect dataset. The goal is not to find the "perfect" dataset or project, but just to get started and iterate from there.

If you take this approach, then you will be on your third iteration of learning and improving while the perfectionists are still in the planning stages!

We also suggest that you iterate from end to end in your project; that is, don't spend months fine-tuning your model, or polishing the perfect GUI, or labelling the perfect dataset… Instead, complete every step as well as you can in a reasonable amount of time, all the way to the end. For instance, if your final goal is an application that runs on a mobile phone, then that should be what you have after each iteration. But perhaps in the early iterations you take some shortcuts, for instance by doing all of the processing on a remote server, and using a simple responsive web application. By completing the project end to end, you will see where the trickiest bits are, and which bits make the biggest difference to the final result.

As you work through this book, we suggest that you complete lots of small experiments, by running and adjusting the notebooks we provide, at the same time that you gradually develop your own projects. That way, you will be getting experience with all of the tools and techniques that we're explaining, as we discuss them.

> s: To make the most of this book, take the time to experiment between each chapter, be it on your own project or by exploring the notebooks we provide. Then try rewriting those notebooks from scratch on a new dataset. It's only by practicing (and failing) a lot that you will get an intuition of how to train a model.

By using the end-to-end iteration approach you will also get a better understanding of how much data you really need. For instance, you may find you can only easily get 200 labeled data items, and you can't really know until you try whether that's enough to get the performance you need for your application to work well in practice.

In an organizational context you will be able to show your colleagues that your idea can really work by showing them a real working prototype. We have repeatedly observed that this is the secret to getting good organizational buy-in for a project.

Since it is easiest to get started on a project where you already have data available, that means it's probably easiest to get started on a project related to something you are already doing, because you already have data about things that you are doing. For instance, if you work in the music business, you may have access to many recordings. If you work as a radiologist, you probably have access to lots of medical images. If you are interested in wildlife preservation, you may have access to lots of images of wildlife.

Sometimes, you have to get a bit creative. Maybe you can find some previous machine learning project, such as a Kaggle competition, that is related to your field of interest. Sometimes, you have to compromise. Maybe you can't find the exact data you need for the precise project you have in mind; but you might be able to find something from a similar domain, or measured in a different way, tackling a slightly different problem. Working on these kinds of similar projects will still give you a good understanding of the overall process, and may help you identify other shortcuts, data sources, and so forth.

Especially when you are just starting out with deep learning, it's not a good idea to branch out into very different areas, to places that deep learning has not been applied to before. That's because if your model does not work at first, you will not know whether it is because you have made a mistake, or if the very problem you are trying to solve is simply not solvable with deep learning. And you won't know where to look to get help. Therefore, it is best at first to start with something where you can find an example online where somebody has had good results with something that is at least somewhat similar to what you are trying to achieve, or where you can convert your data into a format similar to what someone else has used before (such as creating an image from your data). Let's have a look at the state of deep learning, just so you know what kinds of things deep learning is good at right now.

The State of Deep Learning

Let's start by considering whether deep learning can be any good at the problem you are looking to work on. This section provides a summary of the state of deep learning at the start of 2020. However, things move very fast, and by the time you read this some of these constraints may no longer exist. We will try to keep the book's website (https://book.fast.ai/) up-to-date; in addition, a Google search for "what can AI do now" is likely to provide current information.

Computer vision

There are many domains in which deep learning has not been used to analyze images yet, but those where it has been tried have nearly universally shown that computers can recognize what items are in an image at least as well as people can—even specially trained people, such as radiologists. This is known as *object recognition*. Deep learning is also good at recognizing where objects in an image are, and can highlight their locations and name each found object. This is known as *object detection* (there is also a variant of this that we saw in <>, where every pixel is categorized based on what kind of object it is part of—this is called *segmentation*). Deep learning algorithms are generally not good at recognizing images that are significantly different in structure or style to those used to train the model. For instance, if there were no black-and-white images in the training data, the model may do poorly on black-and-white images. Similarly, if the training data did not contain hand-drawn images, then the model will probably do poorly on hand-drawn images. There is no general way to check what types of images are missing in your training set, but we will show in this chapter some ways to try to recognize when unexpected image types arise in the data when the model is being used in production (this is known as checking for *out-of-domain* data).

One major challenge for object detection systems is that image labelling can be slow and expensive. There is a lot of work at the moment going into tools to try to make this labelling faster and easier, and to require fewer handcrafted labels to train accurate object detection models. One approach that is particularly helpful is to synthetically generate variations of input images, such as by rotating them or changing their brightness and contrast; this is called *data augmentation* and also works well for text and other types of models. We will be discussing it in detail in this chapter.

Another point to consider is that although your problem might not look like a computer vision problem, it might be possible with a little imagination to turn it into one. For instance, if what you are trying to classify are sounds, you might try converting the sounds into images of their acoustic waveforms and then training a model on those images.

Text (natural language processing)

Computers are very good at classifying both short and long documents based on categories such as spam or not spam, sentiment (e.g., is the review positive or negative), author, source website, and so forth. We are not aware of any rigorous work done in this area to compare them to humans, but anecdotally it seems to us that deep learning performance is similar to human performance on these tasks. Deep learning is also very good at generating context-appropriate text, such as replies to social media posts, and imitating a particular author's style. It's good at making this content compelling to humans too—in fact, even more compelling than human-generated text. However, deep learning is currently not good at generating *correct* responses! We don't currently have a reliable way to, for instance, combine a knowledge base of medical information with a deep learning model for generating medically correct natural language responses. This is very dangerous, because it is so easy to create content that appears to a layman to be compelling, but actually is entirely incorrect.

Another concern is that context-appropriate, highly compelling responses on social media could be used at massive scale—thousands of times greater than any troll farm previously seen—to spread disinformation, create unrest, and encourage conflict. As a rule of thumb, text generation models will always be technologically a bit ahead of models recognizing automatically generated text. For instance, it is possible to use a model that can recognize artificially generated content to actually improve the generator that creates that content, until the classification model is no longer able to complete its task.

Despite these issues, deep learning has many applications in NLP: it can be used to translate text from one language to another, summarize long documents into something that can be digested more quickly, find all mentions of a concept of interest, and more. Unfortunately, the translation or summary could well include completely incorrect information! However, the performance is already good enough that many people are using these systems—for instance, Google's online translation system (and every other online service we are aware of) is based on deep learning.

Combining text and images

The ability of deep learning to combine text and images into a single model is, generally, far better than most people intuitively expect. For example, a deep learning model can be trained on input images with output captions written in English, and can learn to generate surprisingly appropriate captions automatically for new images! But again, we have the same warning that we discussed in the previous section: there is no guarantee that these captions will actually be correct.

Because of this serious issue, we generally recommend that deep learning be used not as an entirely automated process, but as part of a process in which the model and a human user interact closely. This can potentially make humans orders of magnitude more productive than they would be with entirely manual methods, and actually result in more accurate processes than using a human alone. For instance, an automatic system can be used to identify potential stroke victims directly from CT scans, and send a high-priority alert to have those scans looked at quickly. There is only a three-hour window to treat strokes, so this fast feedback loop could save lives. At the same time, however, all scans could continue to be sent to radiologists in the usual way, so there would be no reduction in human input. Other deep learning models could automatically measure items seen on the scans, and insert those measurements into reports, warning the radiologists about findings that they may have missed, and telling them about other cases that might be relevant.

Tabular data

For analyzing time series and tabular data, deep learning has recently been making great strides. However, deep learning is generally used as part of an ensemble of multiple types of model. If you already have a system that is using random forests or gradient boosting machines (popular tabular modeling tools that you will learn about soon), then switching to or adding deep learning may not result in any dramatic improvement. Deep learning does greatly increase the variety of columns that you can include—for example, columns containing natural language (book titles, reviews, etc.), and high-cardinality categorical columns (i.e., something that contains a large number of discrete choices, such as zip code or product ID). On the down side, deep learning models generally take longer to train than random forests or gradient boosting machines, although this is changing thanks to libraries such as RAPIDS (https://rapids.ai/), which provides GPU acceleration for the whole modeling pipeline. We cover the pros and cons of all these methods in detail in <>.

Recommendation systems

Recommendation systems are really just a special type of tabular data. In particular, they generally have a high-cardinality categorical variable representing users, and another one representing products (or something similar). A company like Amazon represents every purchase that has ever been made by its customers as a giant sparse matrix, with customers as the rows and products as the columns. Once they have the data in this format, data scientists apply some form of collaborative filtering to *fill in the matrix*. For example, if customer A buys products 1 and 10, and customer B buys products 1, 2, 4, and 10, the engine will recommend that A buy 2 and 4. Because deep learning models are good at handling high-cardinality categorical variables, they are quite good at handling recommendation systems. They particularly come into their own, just like for tabular data, when combining these variables with other kinds of data, such as natural language or images. They can also do a good job of combining all of these types of information with additional metadata represented as tables, such as user information, previous transactions, and so forth.

However, nearly all machine learning approaches have the downside that they only tell you what products a particular user might like, rather than what recommendations would be helpful for a user. Many kinds of recommendations for products a user might like may not be at all helpful—for instance, if the user is already familiar with the products, or if they are simply different packagings of products they have already purchased (such as a boxed set of novels, when they already have each of the items in that set). Jeremy likes reading books by Terry Pratchett, and for a while Amazon was recommending nothing but Terry Pratchett books to him (see <>), which really wasn't helpful because he already was aware of these books!

Terry Pratchett books recommendation

Other data types

Often you will find that domain-specific data types fit very nicely into existing categories. For instance, protein chains look a lot like natural language documents, in that they are long sequences of discrete tokens with complex relationships and meaning throughout the sequence. And indeed, it does turn out that using NLP deep learning methods is the current state-of-the-art approach for many types of protein analysis. As another example, sounds can be represented as spectrograms, which can be treated as images; standard deep learning approaches for images turn out to work really well on spectrograms.

The Drivetrain Approach

There are many accurate models that are of no use to anyone, and many inaccurate models that are highly useful. To ensure that your modeling work is useful in practice, you need to consider how your work will be used. In 2012 Jeremy, along with Margit Zwemer and Mike Loukides, introduced a method called *the Drivetrain Approach* for thinking about this issue.

The Drivetrain Approach, illustrated in <>, was described in detail in "Designing Great Data Products" (https://www.oreilly.com/radar/drivetrain-approach-data-products/). The basic idea is to start with considering your objective, then think about what actions you can take to meet that objective and what data you have (or can acquire) that can help, and then build a model that you can use to determine the best actions to take to get the best results in terms of your objective.

Consider a model in an autonomous vehicle: you want to help a car drive safely from point A to point B without human intervention. Great predictive modeling is an important part of the solution, but it doesn't stand on its own; as products become more sophisticated, it disappears into the plumbing. Someone using a self-driving car is completely unaware of the hundreds (if not thousands) of models and the petabytes of data that make it work. But as data scientists build increasingly sophisticated products, they need a systematic design approach.

We use data not just to generate more data (in the form of predictions), but to produce *actionable outcomes*. That is the goal of the Drivetrain Approach. Start by defining a clear *objective*. For instance, Google, when creating their first search engine, considered "What is the user's main objective in typing in a search query?" This led them to their objective, which was to "show the most relevant search result." The next step is to consider what *levers* you can pull (i.e., what actions you can take) to better achieve that objective. In Google's case, that was the ranking of the search results. The third step was to consider what new *data* they would need to produce such a ranking; they realized that the implicit information regarding which pages linked to which other pages could be used for this purpose. Only after these first three steps do we begin thinking about building the predictive *models*. Our objective and available levers, what data we already have and what additional data we will need to collect, determine the models we can build. The models will take both the levers and any uncontrollable variables as their inputs; the outputs from the models can be combined to predict the final state for our objective.

Let's consider another example: recommendation systems. The *objective* of a recommendation engine is to drive additional sales by surprising and delighting the customer with recommendations of items they would not have purchased without the recommendation. The *lever* is the ranking of the recommendations. New *data* must be collected to generate recommendations that will *cause new sales*. This will require conducting many randomized experiments in order to collect data about a wide range of recommendations for a wide range of customers. This is a step that few organizations take; but without it, you don't have the information you need to actually optimize recommendations based on your true objective (more sales!).

Finally, you could build two *models* for purchase probabilities, conditional on seeing or not seeing a recommendation. The difference between these two probabilities is a utility function for a given recommendation to a customer. It will be low in cases where the algorithm recommends a familiar book that the customer has already rejected (both components are small) or a book that they would have bought even without the recommendation (both components are large and cancel each other out).

As you can see, in practice often the practical implementation of your models will require a lot more than just training a model! You'll often need to run experiments to collect more data, and consider how to incorporate your models into the overall system you're developing. Speaking of data, let's now focus on how to find data for your project.

Gathering Data

For many types of projects, you may be able to find all the data you need online. The project we'll be completing in this chapter is a *bear detector*. It will discriminate between three types of bear: grizzly, black, and teddy bears. There are many images on the internet of each type of bear that we can use. We just need a way to find them and download them. We've provided a tool you can use for this purpose, so you can follow along with this chapter and create your own image recognition application for whatever kinds of objects you're interested in. In the fast.ai course, thousands of students have presented their work in the course forums, displaying everything from hummingbird varieties in Trinidad to bus types in Panama—one student even created an application that would help his fiancée recognize his 16 cousins during Christmas vacation!

At the time of writing, Bing Image Search is the best option we know of for finding and downloading images. It's free for up to 1,000 queries per month, and each query can download up to 150 images. However, something better might have come along between when we wrote this and when you're reading the book, so be sure to check out the book's website (https://book.fast.ai/) for our current recommendation.

> important: Keeping in Touch With the Latest Services: Services that can be used for creating datasets come and go all the time, and their features, interfaces, and pricing change regularly too. In this section, we'll show how to use the Bing Image Search API available as part of Azure Cognitive Services at the time this book was written. We'll be providing more options and more up to date information on the book's website (https://book.fast.ai/), so be sure to have a look there now to get the most current information on how to download images from the web to create a dataset for deep learning.

clean

To download images with Bing Image Search, sign up at Microsoft for a free account. You will be given a key, which you can copy and enter in a cell as follows (replacing 'XXX' with your key and executing it):

```
In [ ]: key = os.environ.get('AZURE_SEARCH_KEY', 'XXX')
```

Or, if you're comfortable at the command line, you can set it in your terminal with:

```
export AZURE_SEARCH_KEY=your_key_here
```

and then restart Jupyter Notebook, and use the above line without editing it.

Once you've set `key` , you can use `search_images_bing` . This function is provided by the small `utils` class included with the notebooks online. If you're not sure where a function is defined, you can just type it in your notebook to find out:

```
In [ ]: search_images_bing

Out[ ]: <function utils.search_images_bing(key, term, min_sz=128)>
```

```
In [ ]: results = search_images_bing(key, 'grizzly bear')
        ims = results.attrgot('content_url')
        len(ims)

Out[ ]: 150
```

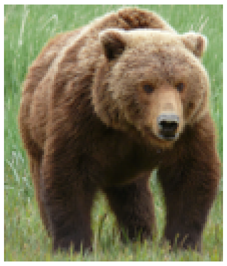
We've successfully downloaded the URLs of 150 grizzly bears (or, at least, images that Bing Image Search finds for that search term). Let's look at one:

```
In [ ]: #hide
        ims = ['http://3.bp.blogspot.com/-S1scRCkI3vY/UHzV2kucsPI/AAAAAAAAA-k/YQ
        5UzHEm9Ss/s1600/Grizzly%2BBear%2BWildlife.jpg']
```

```
In [ ]: dest = 'images/grizzly.jpg'
        download_url(ims[0], dest)
```

```
In [ ]: im = Image.open(dest)
        im.to_thumb(128,128)
```

Out[ ]:



This seems to have worked nicely, so let's use fastai's `download_images` to download all the URLs for each of our search terms. We'll put each in a separate folder:

```
In [ ]: bear_types = 'grizzly','black','teddy'
        path = Path('bears')
```

```
In [ ]: if not path.exists():
            path.mkdir()
            for o in bear_types:
                dest = (path/o)
                dest.mkdir(exist_ok=True)
                results = search_images_bing(key, f'{o} bear')
                download_images(dest, urls=results.attrgot('content_url'))
```

Our folder has image files, as we'd expect:

```
In [ ]: fns = get_image_files(path)
        fns
```

```
Out[ ]: (#421) [Path('bears/black/00000095.jpg'),Path('bears/black/00000133.jp
        g'),Path('bears/black/00000062.jpg'),Path('bears/black/00000023.jpg'),P
        ath('bears/black/00000029.jpg'),Path('bears/black/00000094.jpg'),Path
        ('bears/black/00000124.jpg'),Path('bears/black/00000056.jpeg'),Path('be
        ars/black/00000046.jpg'),Path('bears/black/00000045.jpg')...]
```

> j: I just love this about working in Jupyter notebooks! It's so easy to gradually build what I want, and check my work every step of the way. I make a *lot* of mistakes, so this is really helpful to me...

Often when we download files from the internet, there are a few that are corrupt. Let's check:

In [ ]:
```
failed = verify_images(fns)
failed
```

Out[ ]:
```
(#0) []
```

To remove all the failed images, you can use `unlink` on each of them. Note that, like most fastai functions that return a collection, `verify_images` returns an object of type `L`, which includes the `map` method. This calls the passed function on each element of the collection:

In [ ]:
```
failed.map(Path.unlink);
```

Sidebar: Getting Help in Jupyter Notebooks

Jupyter notebooks are great for experimenting and immediately seeing the results of each function, but there is also a lot of functionality to help you figure out how to use different functions, or even directly look at their source code. For instance, if you type in a cell:

```
??verify_images
```

a window will pop up with:

```
Signature: verify_images(fns)
Source:
def verify_images(fns):
    "Find images in `fns` that can't be opened"
    return L(fns[i] for i,o in
             enumerate(parallel(verify_image, fns)) if not o)
File:      ~/git/fastai/fastai/vision/utils.py
Type:      function
```

This tells us what argument the function accepts (`fns`), then shows us the source code and the file it comes from. Looking at that source code, we can see it applies the function `verify_image` in parallel and only keeps the image files for which the result of that function is `False` , which is consistent with the doc string: it finds the images in `fns` that can't be opened.

Here are some other features that are very useful in Jupyter notebooks:

- At any point, if you don't remember the exact spelling of a function or argument name, you can press Tab to get autocompletion suggestions.
- When inside the parentheses of a function, pressing Shift and Tab simultaneously will display a window with the signature of the function and a short description. Pressing these keys twice will expand the documentation, and pressing them three times will open a full window with the same information at the bottom of your screen.
- In a cell, typing `?func_name` and executing will open a window with the signature of the function and a short description.
- In a cell, typing `??func_name` and executing will open a window with the signature of the function, a short description, and the source code.
- If you are using the fastai library, we added a `doc` function for you: executing `doc(func_name)` in a cell will open a window with the signature of the function, a short description and links to the source code on GitHub and the full documentation of the function in the library docs (https://docs.fast.ai).
- Unrelated to the documentation but still very useful: to get help at any point if you get an error, type `%debug` in the next cell and execute to open the Python debugger (https://docs.python.org/3/library/pdb.html), which will let you inspect the content of every variable.

End sidebar

One thing to be aware of in this process: as we discussed in <>, models can only reflect the data used to train them. And the world is full of biased data, which ends up reflected in, for example, Bing Image Search (which we used to create our dataset). For instance, let's say you were interested in creating an app that could help users figure out whether they had healthy skin, so you trained a model on the results of searches for (say) "healthy skin." <> shows you the kinds of results you would get.

With this as your training data, you would end up not with a healthy skin detector, but a *young white woman touching her face* detector! Be sure to think carefully about the types of data that you might expect to see in practice in your application, and check carefully to ensure that all these types are reflected in your model's source data. footnote:[Thanks to Deb Raji, who came up with the "healthy skin" example. See her paper "Actionable Auditing: Investigating the Impact of Publicly Naming Biased Performance Results of Commercial AI Products" (https://dl.acm.org/doi/10.1145/3306618.3314244) for more fascinating insights into model bias.]

Now that we have downloaded some data, we need to assemble it in a format suitable for model training. In fastai, that means creating an object called `DataLoaders` .

From Data to DataLoaders

`DataLoaders` is a thin class that just stores whatever `DataLoader` objects you pass to it, and makes them available as `train` and `valid` . Although it's a very simple class, it's very important in fastai: it provides the data for your model. The key functionality in `DataLoaders` is provided with just these four lines of code (it has some other minor functionality we'll skip over for now):

```
class DataLoaders(GetAttr):
    def __init__(self, *loaders): self.loaders = loaders
    def __getitem__(self, i): return self.loaders[i]
    train,valid = add_props(lambda i,self: self[i])
```

jargon: DataLoaders: A fastai class that stores multiple `DataLoader` objects you pass to it, normally a `train` and a `valid` , although it's possible to have as many as you like. The first two are made available as properties.

Later in the book you'll also learn about the `Dataset` and `Datasets` classes, which have the same relationship.

To turn our downloaded data into a `DataLoaders` object we need to tell fastai at least four things:

- What kinds of data we are working with
- How to get the list of items
- How to label these items
- How to create the validation set

So far we have seen a number of *factory methods* for particular combinations of these things, which are convenient when you have an application and data structure that happen to fit into those predefined methods. For when you don't, fastai has an extremely flexible system called the *data block API*. With this API you can fully customize every stage of the creation of your `DataLoaders`. Here is what we need to create a `DataLoaders` for the dataset that we just downloaded:

```
In [ ]: bears = DataBlock(
            blocks=(ImageBlock, CategoryBlock),
            get_items=get_image_files,
            splitter=RandomSplitter(valid_pct=0.2, seed=42),
            get_y=parent_label,
            item_tfms=Resize(128))
```

Let's look at each of these arguments in turn. First we provide a tuple where we specify what types we want for the independent and dependent variables:

```
blocks=(ImageBlock, CategoryBlock)
```

The *independent variable* is the thing we are using to make predictions from, and the *dependent variable* is our target. In this case, our independent variables are images, and our dependent variables are the categories (type of bear) for each image. We will see many other types of block in the rest of this book.

For this `DataLoaders` our underlying items will be file paths. We have to tell fastai how to get a list of those files. The `get_image_files` function takes a path, and returns a list of all of the images in that path (recursively, by default):

```
get_items=get_image_files
```

Often, datasets that you download will already have a validation set defined. Sometimes this is done by placing the images for the training and validation sets into different folders. Sometimes it is done by providing a CSV file in which each filename is listed along with which dataset it should be in. There are many ways that this can be done, and fastai provides a very general approach that allows you to use one of its predefined classes for this, or to write your own. In this case, however, we simply want to split our training and validation sets randomly. However, we would like to have the same training/validation split each time we run this notebook, so we fix the random seed (computers don't really know how to create random numbers at all, but simply create lists of numbers that look random; if you provide the same starting point for that list each time—called the *seed*—then you will get the exact same list each time):

```
splitter=RandomSplitter(valid_pct=0.2, seed=42)
```

The independent variable is often referred to as `x` and the dependent variable is often referred to as `y`. Here, we are telling fastai what function to call to create the labels in our dataset:

```
get_y=parent_label
```

`parent_label` is a function provided by fastai that simply gets the name of the folder a file is in. Because we put each of our bear images into folders based on the type of bear, this is going to give us the labels that we need.

Our images are all different sizes, and this is a problem for deep learning: we don't feed the model one image at a time but several of them (what we call a *mini-batch*). To group them in a big array (usually called a *tensor*) that is going to go through our model, they all need to be of the same size. So, we need to add a transform which will resize these images to the same size. *Item transforms* are pieces of code that run on each individual item, whether it be an image, category, or so forth. fastai includes many predefined transforms; we use the `Resize` transform here:

```
item_tfms=Resize(128)
```

This command has given us a `DataBlock` object. This is like a *template* for creating a `DataLoaders`. We still need to tell fastai the actual source of our data—in this case, the path where the images can be found:

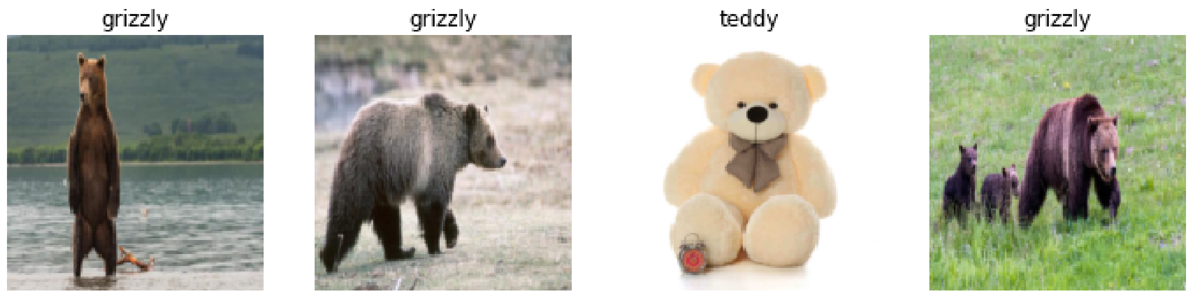
```
In [ ]: dls = bears.dataloaders(path)
```

A `DataLoaders` includes validation and training `DataLoader` s. `DataLoader` is a class that provides batches of a few items at a time to the GPU. We'll be learning a lot more about this class in the next chapter. When you loop through a `DataLoader` fastai will give you 64 (by default) items at a time, all stacked up into a single tensor. We can take a look at a few of those items by calling the `show_batch` method on a `DataLoader` :

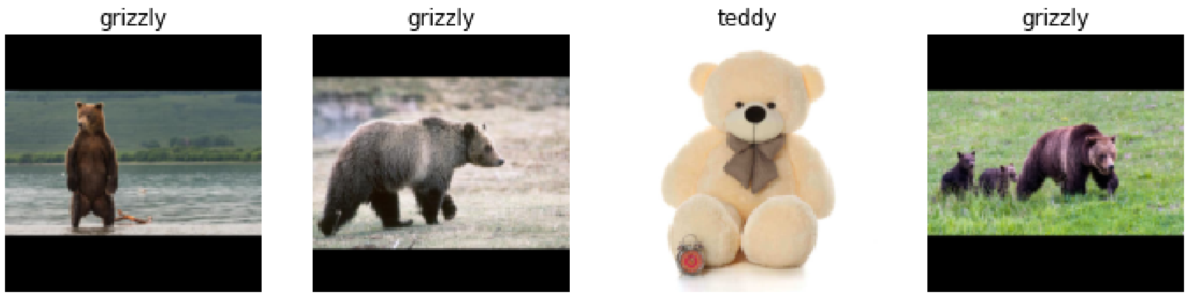
```
In [ ]: dls.valid.show_batch(max_n=4, nrows=1)
```

By default `Resize` *crops* the images to fit a square shape of the size requested, using the full width or height. This can result in losing some important details. Alternatively, you can ask fastai to pad the images with zeros (black), or squish/stretch them:

```
In [ ]: bears = bears.new(item_tfms=Resize(128, ResizeMethod.Squish))
        dls = bears.dataloaders(path)
        dls.valid.show_batch(max_n=4, nrows=1)
```



```
In [ ]: bears = bears.new(item_tfms=Resize(128, ResizeMethod.Pad, pad_mode='zero
s'))
dls = bears.dataloaders(path)
dls.valid.show_batch(max_n=4, nrows=1)
```



All of these approaches seem somewhat wasteful, or problematic. If we squish or stretch the images they end up as unrealistic shapes, leading to a model that learns that things look different to how they actually are, which we would expect to result in lower accuracy. If we crop the images then we remove some of the features that allow us to perform recognition. For instance, if we were trying to recognize breeds of dog or cat, we might end up cropping out a key part of the body or the face necessary to distinguish between similar breeds. If we pad the images then we have a whole lot of empty space, which is just wasted computation for our model and results in a lower effective resolution for the part of the image we actually use.

Instead, what we normally do in practice is to randomly select part of the image, and crop to just that part. On each epoch (which is one complete pass through all of our images in the dataset) we randomly select a different part of each image. This means that our model can learn to focus on, and recognize, different features in our images. It also reflects how images work in the real world: different photos of the same thing may be framed in slightly different ways.

In fact, an entirely untrained neural network knows nothing whatsoever about how images behave. It doesn't even recognize that when an object is rotated by one degree, it still is a picture of the same thing! So actually training the neural network with examples of images where the objects are in slightly different places and slightly different sizes helps it to understand the basic concept of what an object is, and how it can be represented in an image.

Here's another example where we replace `Resize` with `RandomResizedCrop` , which is the transform that provides the behavior we just described. The most important parameter to pass in is `min_scale` , which determines how much of the image to select at minimum each time:

```
In [ ]: bears = bears.new(item_tfms=RandomResizedCrop(128, min_scale=0.3))
dls = bears.dataloaders(path)
dls.train.show_batch(max_n=4, nrows=1, unique=True)
```