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

In [ ]:
```
#hide
from fastbook import *
from kaggle import api
from pandas.api.types import is_string_dtype, is_numeric_dtype, is_categ
orical_dtype
from fastai.tabular.all import *
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from dtreeviz.trees import *
from IPython.display import Image, display_svg, SVG

pd.options.display.max_rows = 20
pd.options.display.max_columns = 8
```

```
Warning: Your Kaggle API key is readable by other users on this system!
To fix this, you can run 'chmod 600 /home/sgugger/.kaggle/kaggle.json'
```

[[chapter_tabular]]

Tabular Modeling Deep Dive

Tabular modeling takes data in the form of a table (like a spreadsheet or CSV). The objective is to predict the value in one column based on the values in the other columns. In this chapter we will not only look at deep learning but also more general machine learning techniques like random forests, as they can give better results depending on your problem.

We will look at how we should preprocess and clean the data as well as how to interpret the result of our models after training, but first, we will see how we can feed columns that contain categories into a model that expects numbers by using embeddings.

Categorical Embeddings

In tabular data some columns may contain numerical data, like "age," while others contain string values, like "sex." The numerical data can be directly fed to the model (with some optional preprocessing), but the other columns need to be converted to numbers. Since the values in those correspond to different categories, we often call this type of variables *categorical variables*. The first type are called *continuous variables*.

> jargon: Continuous and Categorical Variables: Continuous variables are numerical data, such as "age," that can be directly fed to the model, since you can add and multiply them directly. Categorical variables contain a number of discrete levels, such as "movie ID," for which addition and multiplication don't have meaning (even if they're stored as numbers).

At the end of 2015, the Rossmann sales competition (https://www.kaggle.com/c/rossmann-store-sales) ran on Kaggle. Competitors were given a wide range of information about various stores in Germany, and were tasked with trying to predict sales on a number of days. The goal was to help the company to manage stock properly and be able to satisfy demand without holding unnecessary inventory. The official training set provided a lot of information about the stores. It was also permitted for competitors to use additional data, as long as that data was made public and available to all participants.

One of the gold medalists used deep learning, in one of the earliest known examples of a state-of-the-art deep learning tabular model. Their method involved far less feature engineering, based on domain knowledge, than those of the other gold medalists. The paper, "Entity Embeddings of Categorical Variables" (https://arxiv.org/abs/1604.06737) describes their approach. In an online-only chapter on the book's website (https://book.fast.ai/) we show how to replicate it from scratch and attain the same accuracy shown in the paper. In the abstract of the paper the authors (Cheng Guo and Felix Berkhahn) say:

> : Entity embedding not only reduces memory usage and speeds up neural networks compared with one-hot encoding, but more importantly by mapping similar values close to each other in the embedding space it reveals the intrinsic properties of the categorical variables... [It] is especially useful for datasets with lots of high cardinality features, where other methods tend to overfit... As entity embedding defines a distance measure for categorical variables it can be used for visualizing categorical data and for data clustering.

We have already noticed all of these points when we built our collaborative filtering model. We can clearly see that these insights go far beyond just collaborative filtering, however.

The paper also points out that (as we discussed in the last chapter) an embedding layer is exactly equivalent to placing an ordinary linear layer after every one-hot-encoded input layer. The authors used the diagram in <> to show this equivalence. Note that "dense layer" is a term with the same meaning as "linear layer," and the one-hot encoding layers represent inputs.

Entity embeddings in a neural network

The insight is important because we already know how to train linear layers, so this shows that from the point of view of the architecture and our training algorithm the embedding layer is just another layer. We also saw this in practice in the last chapter, when we built a collaborative filtering neural network that looks exactly like this diagram.

Where we analyzed the embedding weights for movie reviews, the authors of the entity embeddings paper analyzed the embedding weights for their sales prediction model. What they found was quite amazing, and illustrates their second key insight. This is that the embedding transforms the categorical variables into inputs that are both continuous and meaningful.

The images in <> illustrate these ideas. They are based on the approaches used in the paper, along with some analysis we have added.

State embeddings and map

On the left is a plot of the embedding matrix for the possible values of the `State` category. For a categorical variable we call the possible values of the variable its "levels" (or "categories" or "classes"), so here one level is "Berlin," another is "Hamburg," etc. On the right is a map of Germany. The actual physical locations of the German states were not part of the provided data, yet the model itself learned where they must be, based only on the behavior of store sales!

Do you remember how we talked about *distance* between embeddings? The authors of the paper plotted the distance between store embeddings against the actual geographic distance between the stores (see <>). They found that they matched very closely!

Store distances

We've even tried plotting the embeddings for days of the week and months of the year, and found that days and months that are near each other on the calendar ended up close as embeddings too, as shown in <>.

Date embeddings

What stands out in these two examples is that we provide the model fundamentally categorical data about discrete entities (e.g., German states or days of the week), and then the model learns an embedding for these entities that defines a continuous notion of distance between them. Because the embedding distance was learned based on real patterns in the data, that distance tends to match up with our intuitions.

In addition, it is valuable in its own right that embeddings are continuous, because models are better at understanding continuous variables. This is unsurprising considering models are built of many continuous parameter weights and continuous activation values, which are updated via gradient descent (a learning algorithm for finding the minimums of continuous functions).

Another benefit is that we can combine our continuous embedding values with truly continuous input data in a straightforward manner: we just concatenate the variables, and feed the concatenation into our first dense layer. In other words, the raw categorical data is transformed by an embedding layer before it interacts with the raw continuous input data. This is how fastai and Guo and Berkhahn handle tabular models containing continuous and categorical variables.

An example using this concatenation approach is how Google does it recommendations on Google Play, as explained in the paper "Wide & Deep Learning for Recommender Systems" (https://arxiv.org/abs/1606.07792). <> illustrates.

The Google Play recommendation system

Interestingly, the Google team actually combined both approaches we saw in the previous chapter: the dot product (which they call *cross product*) and neural network approaches.

Let's pause for a moment. So far, the solution to all of our modeling problems has been: *train a deep learning model*. And indeed, that is a pretty good rule of thumb for complex unstructured data like images, sounds, natural language text, and so forth. Deep learning also works very well for collaborative filtering. But it is not always the best starting point for analyzing tabular data.

Beyond Deep Learning

Most machine learning courses will throw dozens of different algorithms at you, with a brief technical description of the math behind them and maybe a toy example. You're left confused by the enormous range of techniques shown and have little practical understanding of how to apply them.

The good news is that modern machine learning can be distilled down to a couple of key techniques that are widely applicable. Recent studies have shown that the vast majority of datasets can be best modeled with just two methods:

1. Ensembles of decision trees (i.e., random forests and gradient boosting machines), mainly for structured data (such as you might find in a database table at most companies)
2. Multilayered neural networks learned with SGD (i.e., shallow and/or deep learning), mainly for unstructured data (such as audio, images, and natural language)

Although deep learning is nearly always clearly superior for unstructured data, these two approaches tend to give quite similar results for many kinds of structured data. But ensembles of decision trees tend to train faster, are often easier to interpret, do not require special GPU hardware for inference at scale, and often require less hyperparameter tuning. They have also been popular for quite a lot longer than deep learning, so there is a more mature ecosystem of tooling and documentation around them.

Most importantly, the critical step of interpreting a model of tabular data is significantly easier for decision tree ensembles. There are tools and methods for answering the pertinent questions, like: Which columns in the dataset were the most important for your predictions? How are they related to the dependent variable? How do they interact with each other? And which particular features were most important for some particular observation?

Therefore, ensembles of decision trees are our first approach for analyzing a new tabular dataset.

The exception to this guideline is when the dataset meets one of these conditions:

- There are some high-cardinality categorical variables that are very important ("cardinality" refers to the number of discrete levels representing categories, so a high-cardinality categorical variable is something like a zip code, which can take on thousands of possible levels).
- There are some columns that contain data that would be best understood with a neural network, such as plain text data.

In practice, when we deal with datasets that meet these exceptional conditions, we always try both decision tree ensembles and deep learning to see which works best. It is likely that deep learning will be a useful approach in our example of collaborative filtering, as we have at least two high-cardinality categorical variables: the users and the movies. But in practice things tend to be less cut-and-dried, and there will often be a mixture of high- and low-cardinality categorical variables and continuous variables.

Either way, it's clear that we are going to need to add decision tree ensembles to our modeling toolbox!

Up to now we've used PyTorch and fastai for pretty much all of our heavy lifting. But these libraries are mainly designed for algorithms that do lots of matrix multiplication and derivatives (that is, stuff like deep learning!). Decision trees don't depend on these operations at all, so PyTorch isn't much use.

Instead, we will be largely relying on a library called scikit-learn (also known as `sklearn`). Scikit-learn is a popular library for creating machine learning models, using approaches that are not covered by deep learning. In addition, we'll need to do some tabular data processing and querying, so we'll want to use the Pandas library. Finally, we'll also need NumPy, since that's the main numeric programming library that both sklearn and Pandas rely on.

We don't have time to do a deep dive into all these libraries in this book, so we'll just be touching on some of the main parts of each. For a far more in depth discussion, we strongly suggest Wes McKinney's Python for Data Analysis (http://shop.oreilly.com/product/0636920023784.do) (O'Reilly). Wes is the creator of Pandas, so you can be sure that the information is accurate!

First, let's gather the data we will use.

The Dataset

The dataset we use in this chapter is from the Blue Book for Bulldozers Kaggle competition, which has the following description: "The goal of the contest is to predict the sale price of a particular piece of heavy equipment at auction based on its usage, equipment type, and configuration. The data is sourced from auction result postings and includes information on usage and equipment configurations."

This is a very common type of dataset and prediction problem, similar to what you may see in your project or workplace. The dataset is available for download on Kaggle, a website that hosts data science competitions.

Kaggle Competitions

Kaggle is an awesome resource for aspiring data scientists or anyone looking to improve their machine learning skills. There is nothing like getting hands-on practice and receiving real-time feedback to help you improve your skills.

Kaggle provides:

- Interesting datasets
- Feedback on how you're doing
- A leaderboard to see what's good, what's possible, and what's state-of-the-art
- Blog posts by winning contestants sharing useful tips and techniques

Until now all our datasets have been available to download through fastai's integrated dataset system. However, the dataset we will be using in this chapter is only available from Kaggle. Therefore, you will need to register on the site, then go to the page for the competition (https://www.kaggle.com/c/bluebook-for-bulldozers). On that page click "Rules," then "I Understand and Accept." (Although the competition has finished, and you will not be entering it, you still have to agree to the rules to be allowed to download the data.)

The easiest way to download Kaggle datasets is to use the Kaggle API. You can install this using `pip` by running this in a notebook cell:

```
!pip install kaggle
```

You need an API key to use the Kaggle API; to get one, click on your profile picture on the Kaggle website, and choose My Account, then click Create New API Token. This will save a file called *kaggle.json* to your PC. You need to copy this key on your GPU server. To do so, open the file you downloaded, copy the contents, and paste them in the following cell in the notebook associated with this chapter (e.g., `creds = '{"username":"xxx","key":"xxx"}'`):

In [ ]:
```
creds = ''
```

Then execute this cell (this only needs to be run once):

In [ ]:
```
cred_path = Path('~/.kaggle/kaggle.json').expanduser()
if not cred_path.exists():
    cred_path.parent.mkdir(exist_ok=True)
    cred_path.write(creds)
    cred_path.chmod(0o600)
```

Now you can download datasets from Kaggle! Pick a path to download the dataset to:

In [ ]:
```
path = URLs.path('bluebook')
path
```

Out[ ]:
```
Path('/home/sgugger/.fastai/archive/bluebook')
```

In [ ]:
```
#hide
Path.BASE_PATH = path
```

And use the Kaggle API to download the dataset to that path, and extract it:

```
In [ ]: if not path.exists():
            path.mkdir()
            api.competition_download_cli('bluebook-for-bulldozers', path=path)
            file_extract(path/'bluebook-for-bulldozers.zip')

        path.ls(file_type='text')
```

```
Out[ ]: (#7) [Path('Valid.csv'),Path('Machine_Appendix.csv'),Path('ValidSolutio
        n.csv'),Path('TrainAndValid.csv'),Path('random_forest_benchmark_test.cs
        v'),Path('Test.csv'),Path('median_benchmark.csv')]
```

Now that we have downloaded our dataset, let's take a look at it!

Look at the Data

Kaggle provides information about some of the fields of our dataset. The Data (https://www.kaggle.com/c/bluebook-for-bulldozers/data) explains that the key fields in *train.csv* are:

- `SalesID` :: The unique identifier of the sale.
- `MachineID` :: The unique identifier of a machine. A machine can be sold multiple times.
- `saleprice` :: What the machine sold for at auction (only provided in *train.csv*).
- `saledate` :: The date of the sale.

In any sort of data science work, it's important to *look at your data directly* to make sure you understand the format, how it's stored, what types of values it holds, etc. Even if you've read a description of the data, the actual data may not be what you expect. We'll start by reading the training set into a Pandas DataFrame. Generally it's a good idea to specify `low_memory=False` unless Pandas actually runs out of memory and returns an error. The `low_memory` parameter, which is `True` by default, tells Pandas to only look at a few rows of data at a time to figure out what type of data is in each column. This means that Pandas can actually end up using different data type for different rows, which generally leads to data processing errors or model training problems later.

Let's load our data and have a look at the columns:

```
In [ ]: df = pd.read_csv(path/'TrainAndValid.csv', low_memory=False)
In [ ]: df.columns
```

```
Out[ ]: Index(['SalesID', 'SalePrice', 'MachineID', 'ModelID', 'datasource',
               'auctioneerID', 'YearMade', 'MachineHoursCurrentMeter', 'UsageBa
        nd',
               'saledate', 'fiModelDesc', 'fiBaseModel', 'fiSecondaryDesc',
               'fiModelSeries', 'fiModelDescriptor', 'ProductSize',
               'fiProductClassDesc', 'state', 'ProductGroup', 'ProductGroupDes
        c',
               'Drive_System', 'Enclosure', 'Forks', 'Pad_Type', 'Ride_Contro
        l',
               'Stick', 'Transmission', 'Turbocharged', 'Blade_Extension',
               'Blade_Width', 'Enclosure_Type', 'Engine_Horsepower', 'Hydraulic
        s',
               'Pushblock', 'Ripper', 'Scarifier', 'Tip_Control', 'Tire_Size',
               'Coupler', 'Coupler_System', 'Grouser_Tracks', 'Hydraulics_Flo
        w',
               'Track_Type', 'Undercarriage_Pad_Width', 'Stick_Length', 'Thum
        b',
               'Pattern_Changer', 'Grouser_Type', 'Backhoe_Mounting', 'Blade_Ty
        pe',
               'Travel_Controls', 'Differential_Type', 'Steering_Controls'],
              dtype='object')
```

That's a lot of columns for us to look at! Try looking through the dataset to get a sense of what kind of information is in each one. We'll shortly see how to "zero in" on the most interesting bits.

At this point, a good next step is to handle *ordinal columns*. This refers to columns containing strings or similar, but where those strings have a natural ordering. For instance, here are the levels of `ProductSize`:

```
In [ ]: df['ProductSize'].unique()
```

```
Out[ ]: array([nan, 'Medium', 'Small', 'Large / Medium', 'Mini', 'Large', 'Comp
        act'], dtype=object)
```

We can tell Pandas about a suitable ordering of these levels like so:

```
In [ ]: sizes = 'Large','Large / Medium','Medium','Small','Mini','Compact'
```

```
In [ ]: df['ProductSize'] = df['ProductSize'].astype('category')
        df['ProductSize'].cat.set_categories(sizes, ordered=True, inplace=True)
```

The most important data column is the dependent variable—that is, the one we want to predict. Recall that a model's metric is a function that reflects how good the predictions are. It's important to note what metric is being used for a project. Generally, selecting the metric is an important part of the project setup. In many cases, choosing a good metric will require more than just selecting a variable that already exists. It is more like a design process. You should think carefully about which metric, or set of metrics, actually measures the notion of model quality that matters to you. If no variable represents that metric, you should see if you can build the metric from the variables that are available.

However, in this case Kaggle tells us what metric to use: root mean squared log error (RMSLE) between the actual and predicted auction prices. We need do only a small amount of processing to use this: we take the log of the prices, so that `rmse` of that value will give us what we ultimately need:

```
In [ ]: dep_var = 'SalePrice'
```

```
In [ ]: df[dep_var] = np.log(df[dep_var])
```

We are now ready to explore our first machine learning algorithm for tabular data: decision trees.

Decision Trees

Decision tree ensembles, as the name suggests, rely on decision trees. So let's start there! A decision tree asks a series of binary (that is, yes or no) questions about the data. After each question the data at that part of the tree is split between a "yes" and a "no" branch, as shown in <>. After one or more questions, either a prediction can be made on the basis of all previous answers or another question is required.

An example of decision tree

This sequence of questions is now a procedure for taking any data item, whether an item from the training set or a new one, and assigning that item to a group. Namely, after asking and answering the questions, we can say the item belongs to the same group as all the other training data items that yielded the same set of answers to the questions. But what good is this? The goal of our model is to predict values for items, not to assign them into groups from the training dataset. The value is that we can now assign a prediction value for each of these groups—for regression, we take the target mean of the items in the group.

Let's consider how we find the right questions to ask. Of course, we wouldn't want to have to create all these questions ourselves—that's what computers are for! The basic steps to train a decision tree can be written down very easily:

1. Loop through each column of the dataset in turn.
2. For each column, loop through each possible level of that column in turn.
3. Try splitting the data into two groups, based on whether they are greater than or less than that value (or if it is a categorical variable, based on whether they are equal to or not equal to that level of that categorical variable).
4. Find the average sale price for each of those two groups, and see how close that is to the actual sale price of each of the items of equipment in that group. That is, treat this as a very simple "model" where our predictions are simply the average sale price of the item's group.
5. After looping through all of the columns and all the possible levels for each, pick the split point that gave the best predictions using that simple model.
6. We now have two different groups for our data, based on this selected split. Treat each of these as separate datasets, and find the best split for each by going back to step 1 for each group.
7. Continue this process recursively, until you have reached some stopping criterion for each group—for instance, stop splitting a group further when it has only 20 items in it.

Although this is an easy enough algorithm to implement yourself (and it is a good exercise to do so), we can save some time by using the implementation built into sklearn.

First, however, we need to do a little data preparation.

> A: Here's a productive question to ponder. If you consider that the procedure for defining a decision tree essentially chooses one *sequence of splitting questions about variables*, you might ask yourself, how do we know this procedure chooses the *correct sequence*? The rule is to choose the splitting question that produces the best split (i.e., that most accurately separates the items into two distinct categories), and then to apply the same rule to the groups that split produces, and so on. This is known in computer science as a "greedy" approach. Can you imagine a scenario in which asking a “less powerful” splitting question would enable a better split down the road (or should I say down the trunk!) and lead to a better result overall?

Handling Dates

The first piece of data preparation we need to do is to enrich our representation of dates. The fundamental basis of the decision tree that we just described is *bisection*— dividing a group into two. We look at the ordinal variables and divide up the dataset based on whether the variable's value is greater (or lower) than a threshold, and we look at the categorical variables and divide up the dataset based on whether the variable's level is a particular level. So this algorithm has a way of dividing up the dataset based on both ordinal and categorical data.

But how does this apply to a common data type, the date? You might want to treat a date as an ordinal value, because it is meaningful to say that one date is greater than another. However, dates are a bit different from most ordinal values in that some dates are qualitatively different from others in a way that that is often relevant to the systems we are modeling.

In order to help our algorithm handle dates intelligently, we'd like our model to know more than whether a date is more recent or less recent than another. We might want our model to make decisions based on that date's day of the week, on whether a day is a holiday, on what month it is in, and so forth. To do this, we replace every date column with a set of date metadata columns, such as holiday, day of week, and month. These columns provide categorical data that we suspect will be useful.

fastai comes with a function that will do this for us—we just have to pass a column name that contains dates:

```
In [ ]: df = add_datepart(df, 'saledate')
```

Let's do the same for the test set while we're there:

```
In [ ]: df_test = pd.read_csv(path/'Test.csv', low_memory=False)
        df_test = add_datepart(df_test, 'saledate')
```

We can see that there are now lots of new columns in our DataFrame:

```
In [ ]: ' '.join(o for o in df.columns if o.startswith('sale'))

Out[ ]: 'saleYear saleMonth saleWeek saleDay saleDayofweek saleDayofyear saleIs
        _month_end saleIs_month_start saleIs_quarter_end saleIs_quarter_start s
        aleIs_year_end saleIs_year_start saleElapsed'
```

This is a good first step, but we will need to do a bit more cleaning. For this, we will use fastai objects called `TabularPandas` and `TabularProc` .

Using TabularPandas and TabularProc

A second piece of preparatory processing is to be sure we can handle strings and missing data. Out of the box, sklearn cannot do either. Instead we will use fastai's class `TabularPandas`, which wraps a Pandas DataFrame and provides a few conveniences. To populate a `TabularPandas`, we will use two `TabularProc` s, `Categorify` and `FillMissing`. A `TabularProc` is like a regular `Transform`, except that:

- It returns the exact same object that's passed to it, after modifying the object in place.
- It runs the transform once, when data is first passed in, rather than lazily as the data is accessed.

`Categorify` is a `TabularProc` that replaces a column with a numeric categorical column. `FillMissing` is a `TabularProc` that replaces missing values with the median of the column, and creates a new Boolean column that is set to `True` for any row where the value was missing. These two transforms are needed for nearly every tabular dataset you will use, so this is a good starting point for your data processing:

In [ ]:
```
procs = [Categorify, FillMissing]
```

`TabularPandas` will also handle splitting the dataset into training and validation sets for us. However we need to be very careful about our validation set. We want to design it so that it is like the *test set* Kaggle will use to judge the contest.

Recall the distinction between a validation set and a test set, as discussed in <>. A validation set is data we hold back from training in order to ensure that the training process does not overfit on the training data. A test set is data that is held back even more deeply, from us ourselves, in order to ensure that *we* don't overfit on the validation data, as we explore various model architectures and hyperparameters.

We don't get to see the test set. But we do want to define our validation data so that it has the same sort of relationship to the training data as the test set will have.

In some cases, just randomly choosing a subset of your data points will do that. This is not one of those cases, because it is a time series.

If you look at the date range represented in the test set, you will discover that it covers a six-month period from May 2012, which is later in time than any date in the training set. This is a good design, because the competition sponsor will want to ensure that a model is able to predict the future. But it means that if we are going to have a useful validation set, we also want the validation set to be later in time than the training set. The Kaggle training data ends in April 2012, so we will define a narrower training dataset which consists only of the Kaggle training data from before November 2011, and we'll define a validation set consisting of data from after November 2011.

To do this we use `np.where`, a useful function that returns (as the first element of a tuple) the indices of all `True` values:

In [ ]:
```
cond = (df.saleYear<2011) | (df.saleMonth<10)
train_idx = np.where( cond)[0]
valid_idx = np.where(~cond)[0]

splits = (list(train_idx),list(valid_idx))
```

`TabularPandas` needs to be told which columns are continuous and which are categorical. We can handle that automatically using the helper function `cont_cat_split`:

```
In [ ]: cont,cat = cont_cat_split(df, 1, dep_var=dep_var)
```

```
In [ ]: to = TabularPandas(df, procs, cat, cont, y_names=dep_var, splits=splits)
```

A `TabularPandas` behaves a lot like a fastai `Datasets` object, including providing `train` and `valid` attributes:

```
In [ ]: len(to.train),len(to.valid)
```

```
Out[ ]: (404710, 7988)
```

We can see that the data is still displayed as strings for categories (we only show a few columns here because the full table is too big to fit on a page):

```
In [ ]: #hide_output
        to.show(3)
```

	UsageBand	fiModelDesc	fiBaseModel	fiSecondaryDesc	fiModelSeries	fiModelDescriptor	Prc
0	Low	521D	521	D	#na#	#na#	
1	Low	950FII	950	F	II	#na#	
2	High	226	226	#na#	#na#	#na#	

```
In [ ]: #hide_input
        to1 = TabularPandas(df, procs, ['state', 'ProductGroup', 'Drive_System',
        'Enclosure'], [], y_names=dep_var, splits=splits)
        to1.show(3)
```

	state	ProductGroup	Drive_System	Enclosure	SalePrice
0	Alabama	WL	#na#	EROPS w AC	11.097410
1	North Carolina	WL	#na#	EROPS w AC	10.950807
2	New York	SSL	#na#	OROPS	9.210340

However, the underlying items are all numeric:

In [ ]:
```
#hide_output
to.items.head(3)
```

Out[ ]:

	SalesID	SalePrice	MachineID	ModelID	...	saleDay_na	saleDayofweek_na	saleDayofyear_na
0	1139246	11.097410	999089	3157	...	1	1	1
1	1139248	10.950807	117657	77	...	1	1	1
2	1139249	9.210340	434808	7009	...	1	1	1

3 rows × 79 columns

In [ ]:
```
#hide_input
to1.items[['state', 'ProductGroup', 'Drive_System', 'Enclosure']].head(3
)
```

Out[ ]:

	state	ProductGroup	Drive_System	Enclosure
0	1	6	0	3
1	33	6	0	3
2	32	3	0	6

The conversion of categorical columns to numbers is done by simply replacing each unique level with a number. The numbers associated with the levels are chosen consecutively as they are seen in a column, so there's no particular meaning to the numbers in categorical columns after conversion. The exception is if you first convert a column to a Pandas ordered category (as we did for `ProductSize` earlier), in which case the ordering you chose is used. We can see the mapping by looking at the `classes` attribute:

In [ ]:
```
to.classes['ProductSize']
```

Out[ ]:
```
(#7) ['#na#','Large','Large / Medium','Medium','Small','Mini','Compac
t']
```

Since it takes a minute or so to process the data to get to this point, we should save it—that way in the future we can continue our work from here without rerunning the previous steps. fastai provides a `save` method that uses Python's *pickle* system to save nearly any Python object:

In [ ]:
```
(path/'to.pkl').save(to)
```

To read this back later, you would type:

```
to = (path/'to.pkl').load()
```

Now that all this preprocessing is done, we are ready to create a decision tree.

Creating the Decision Tree

To begin, we define our independent and dependent variables:

In [ ]:
```
#hide
to = (path/'to.pkl').load()
```

In [ ]:
```
xs,y = to.train.xs,to.train.y
valid_xs,valid_y = to.valid.xs,to.valid.y
```

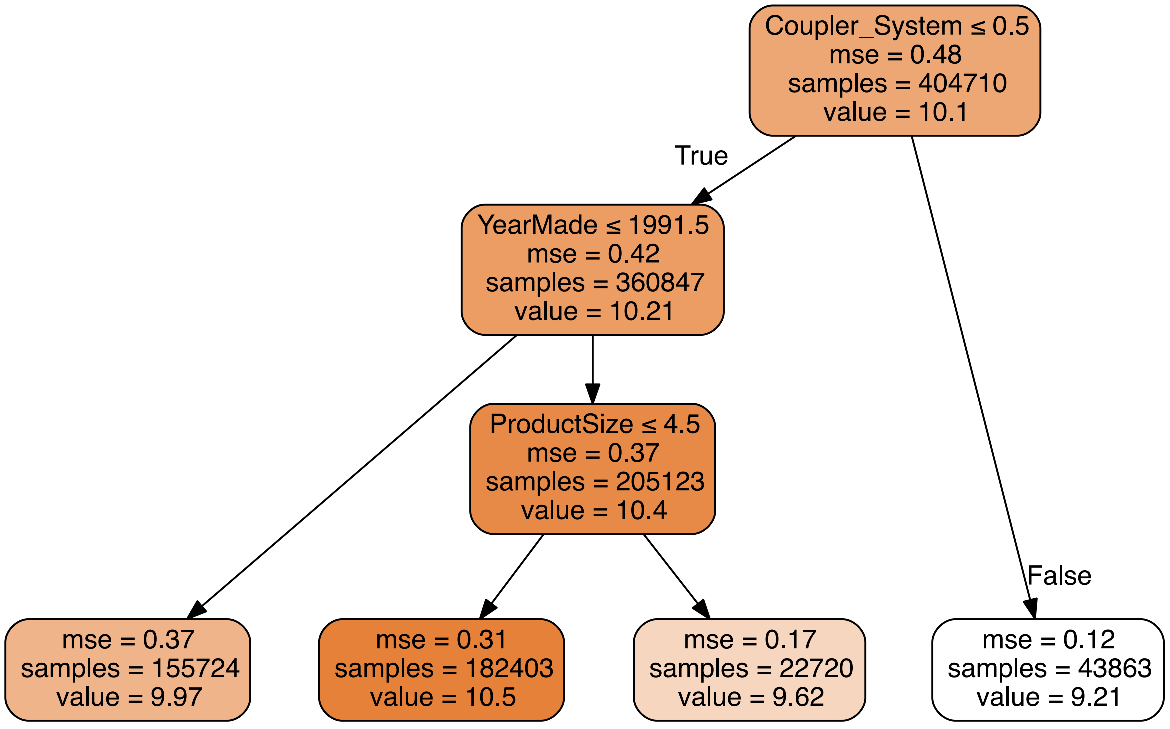
Now that our data is all numeric, and there are no missing values, we can create a decision tree:

In [ ]:
```
m = DecisionTreeRegressor(max_leaf_nodes=4)
m.fit(xs, y);
```

To keep it simple, we've told sklearn to just create four *leaf nodes*. To see what it's learned, we can display the tree:

In [ ]:
```
draw_tree(m, xs, size=7, leaves_parallel=True, precision=2)
```

Out[ ]:



Understanding this picture is one of the best ways to understand decision trees, so we will start at the top and explain each part step by step.

The top node represents the *initial model* before any splits have been done, when all the data is in one group. This is the simplest possible model. It is the result of asking zero questions and will always predict the value to be the average value of the whole dataset. In this case, we can see it predicts a value of 10.10 for the logarithm of the sales price. It gives a mean squared error of 0.48. The square root of this is 0.69. (Remember that unless you see `m_rmse`, or a *root mean squared error*, then the value you are looking at is before taking the square root, so it is just the average of the square of the differences.) We can also see that there are 404,710 auction records in this group—that is the total size of our training set. The final piece of information shown here is the decision criterion for the best split that was found, which is to split based on the `coupler_system` column.

Moving down and to the left, this node shows us that there were 360,847 auction records for equipment where `coupler_system` was less than 0.5. The average value of our dependent variable in this group is 10.21. Moving down and to the right from the initial model takes us to the records where `coupler_system` was greater than 0.5.

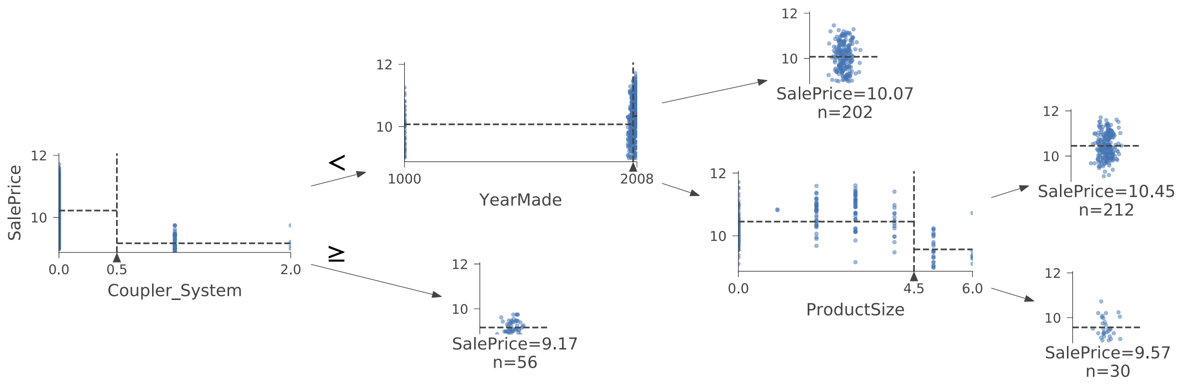
The bottom row contains our *leaf nodes*: the nodes with no answers coming out of them, because there are no more questions to be answered. At the far right of this row is the node containing records where `coupler_system` was greater than 0.5. The average value here is 9.21, so we can see the decision tree algorithm did find a single binary decision that separated high-value from low-value auction results. Asking only about `coupler_system` predicts an average value of 9.21 versus 10.1.

Returning back to the top node after the first decision point, we can see that a second binary decision split has been made, based on asking whether `YearMade` is less than or equal to 1991.5. For the group where this is true (remember, this is now following two binary decisions, based on `coupler_system` and `YearMade`) the average value is 9.97, and there are 155,724 auction records in this group. For the group of auctions where this decision is false, the average value is 10.4, and there are 205,123 records. So again, we can see that the decision tree algorithm has successfully split our more expensive auction records into two more groups which differ in value significantly.

We can show the same information using Terence Parr's powerful [dtreeviz (https://explained.ai/decision-tree-viz/)](https://explained.ai/decision-tree-viz/) library:

In [ ]:
```
samp_idx = np.random.permutation(len(y))[:500]
dtreeviz(m, xs.iloc[samp_idx], y.iloc[samp_idx], xs.columns, dep_var,
        fontname='DejaVu Sans', scale=1.6, label_fontsize=10,
        orientation='LR')
```

Out[ ]:



This shows a chart of the distribution of the data for each split point. We can clearly see that there's a problem with our `YearMade` data: there are bulldozers made in the year 1000, apparently! Presumably this is actually just a missing value code (a value that doesn't otherwise appear in the data and that is used as a placeholder in cases where a value is missing). For modeling purposes, 1000 is fine, but as you can see this outlier makes visualization the values we are interested in more difficult. So, let's replace it with 1950:

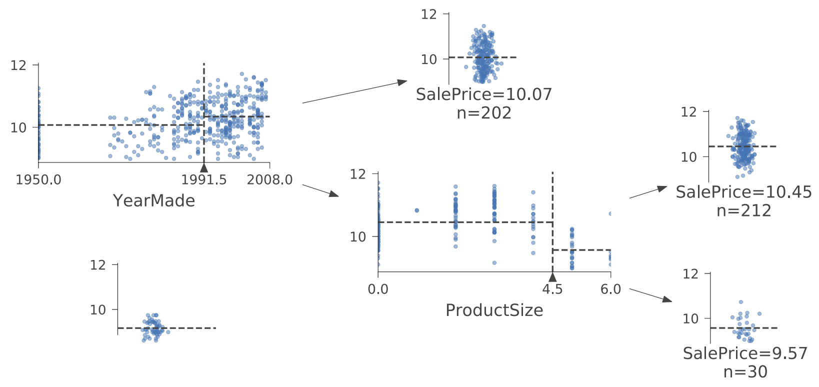
In [ ]:
```
xs.loc[xs['YearMade']<1900, 'YearMade'] = 1950
valid_xs.loc[valid_xs['YearMade']<1900, 'YearMade'] = 1950
```

That change makes the split much clearer in the tree visualization, even although it doesn't actually change the result of the model in any significant way. This is a great example of how resilient decision trees are to data issues!

In [ ]:
```
m = DecisionTreeRegressor(max_leaf_nodes=4).fit(xs, y)

dtreeviz(m, xs.iloc[samp_idx], y.iloc[samp_idx], xs.columns, dep_var,
        fontname='DejaVu Sans', scale=1.6, label_fontsize=10,
        orientation='LR')
```

Out[ ]:


YearMade
SalePrice=10.07
n=202
ProductSize
SalePrice=10.45
n=212
SalePrice=9.57
n=30