DDPM

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We create two new Tensor Types, one for our noise, and one for our timestep.

```
class TensorNoise(TensorImageBase):pass
class TensorStep(TensorBase): pass
```

We would like normalize to denormalize our noise before showing it. This is so the noise in our image looks similar to the noise in our noised image.

```
@Normalize
def decodes(self, x:TensorNoise):
    f = to_cpu if x.device.type=='cpu' else noop
    return (x*f(self.std) + f(self.mean))
```

```
norm = Normalize.from_stats(*imagenet_stats)
show_images(norm.decode(img))
```

I patch ItemTransform here, so that it can work off of TypedTuples. Essentially if we have a `DiffusionTuple`, the transform will apply to that if it should apply to that type of tuple.

```
class ItemTransform(Transform):
    "A transform that always take tuples as items"
    _retain = True
    # Only showing important code
    def _call_tuple(self:ItemTransform, name, x, split_idx=None, **kwargs):
        f = getattr(super(), name)
        f2name='encodes' if name == '__call__' else 'decodes' if name == 'decode' else nam
        f2 = getattr(self, f2name)
        if isinstance(f2,TypeDispatch) and f2[type(x)] is not None:
            if split_idx!=self.split_idx and self.split_idx is not None: return x
            y = f2(x, **kwargs)
        else:
            y = f(list(x), **kwargs)
        return y
```

The general idea is to implement a named tuple, and use duck typing. In the future, we should look at the named tuple class and do something more similar to that.

```
class DiffusionTuple(fastuple):
    def __new__(cls, *rest):
        self=super().__new__(cls, *rest)
        i=0
        self.x=self[i]
        if(isinstance(self[i+1],TensorImage)): self.x0=self[i:=i+1]
        self.t=self[i:=i+1]
        if(len(self)>i+1): self.y=self[i:=i+1]
        if(len(self)>i+1): self.pred=self[i:=i+1]
        return self
```

A little transform to make our tuple a `DiffusionTuple`

```
class ToDiffusionTuple(ItemTransform):
    order=100
    def encodes(self,xy):
        return DiffusionTuple(*xy[:-1],TensorNoise(xy[-1]))
```

This `Transform` expects y to contain an image, and just replaces it with noise. Our model tries to predict the noise in an image.

```
class LabelToNoise(ItemTransform):
    order=101
```

```
    def encodes(self,xy:DiffusionTuple):
        y=xy.y
        xy.y[:]=TensorNoise(torch.randn_like(y))
        return xy
```

```
diff_tuple=LabelToNoise.encodes(DiffusionTuple(img[0].detach().clone(),TensorStep(torch.te
```

We can access tuple elements by attributes. This is useful when you don't know what index a particular value is located.

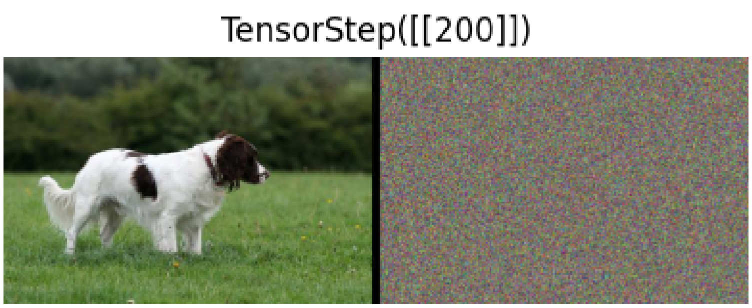
```
diff_tuple.x.shape,diff_tuple.t.shape,diff_tuple.y.shape
```

```
(torch.Size([3, 320, 480]), torch.Size([1, 1]), torch.Size([3, 320, 480]))
```

Now we have a way to create an image, and convert the label to noise.

```
norm.decode(diff_tuple).show(show_noise=True)
```

```
<AxesSubplot:title={'center':'TensorStep([[200]])'}>
```



Next, we need to go create a noised image, to pass to our model.

```
class Diffusion_P_Sampler():
    def __init__(self,model,sampling_function):
        self.device=sampling_function.device
        self.model=model
        self.sampling_function=sampling_function
    # __call__ implemented, but not shown.
```

```
    def iter_noise(self,x_t,ts,t_start):
        i=0
        while((ts>0).any()):
            x,t=x_t[ts>0],ts[ts>0]
            with autocast(device_type=self.device, dtype=x.dtype):
                with torch.no_grad():
                    e = self.model(x,self.deconvert(t) if i!=0 else t_start)
                x_t[ts>0]=self.sampling_function(x,e,t,t=t_start if i==0 else None)
            ts[ts>0]-=1
            i+=1
            yield x_t
```

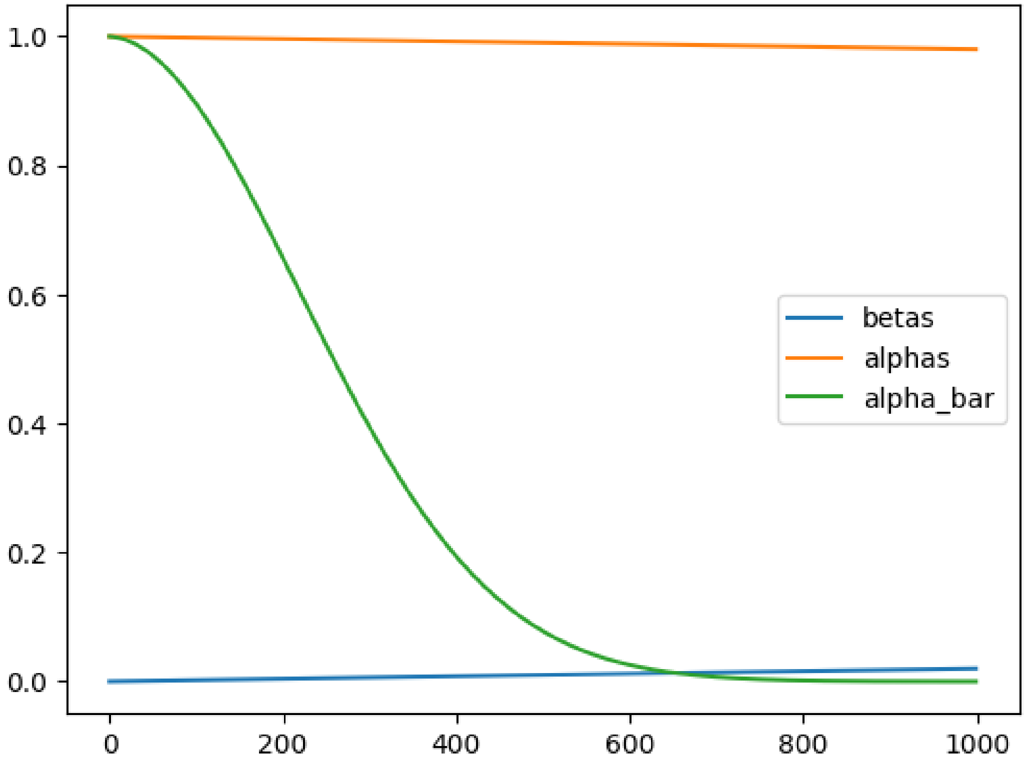
Next we need to know how much noise to apply to each step.

```
class LinearNoiseSchedule:
    "Schedule like used in DDPM"
    def __init__(self,betas=None,n_steps=None,device='cuda'):
        if betas is not None: self.n_steps=betas.shape[0]
        if n_steps is None: self.n_steps=1000
        if betas is None: self.betas = torch.linspace(0.0001, 0.02, self.n_steps,device=de
        self.alphas = 1. - self.betas
        self.alpha_bar = torch.cumprod(self.alphas, dim=0)
```

Lets graph the various values here, in order to see what happens. Pay particularly close attention to `alpha_bar` as that controls the balance betwen our signal(image) and our noise.

```
lns=LinearNoiseSchedule()
plt.plot((lns.betas).cpu())
plt.plot((lns.alphas).cpu())
plt.plot((lns.alpha_bar).cpu())
plt.legend(['betas', 'alphas','alpha_bar'])
```

```
<matplotlib.legend.Legend at 0x7f74f2a22e00>
```



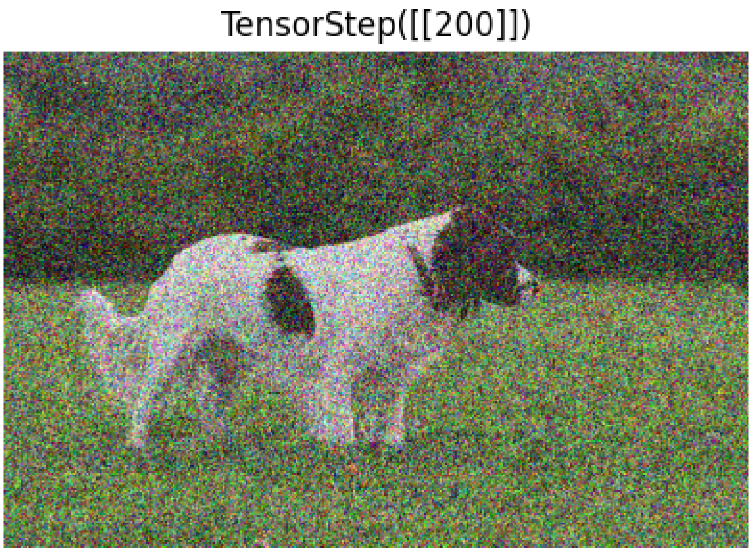
Next is DDPM-style Q-sampling. This is pretty much used for all diffusion models, and is the process that takes us from and image to noise.

```
class DDPM_Q_Sampling():
    def __init__(self,predicts_x=False,noise_schedule=LinearNoiseSchedule(),n_steps=1000,d
        self.device=device
        self.ns=noise_schedule
        self.n_steps=n_steps
        self.t_sched=torch.linspace(0,len(self.ns.alpha_bar)-1,n_steps,dtype=torch.long)[.
    def __call__(self,x,es,t):
        t=self.t_sched[t]
        a=self.ns.alpha_bar[t].to(device=x.device)
        signal = (a ** .5)*x
        noise = (1-a)**.5 * es
        return signal + noise
```

```
diff_trans = DiffusionSamplingTransform(DDPM_Q_Sampling(),lambda x:x)
```

```
norm.decode(diff_trans(diff_tuple)).show()
```

```
<AxesSubplot:title={'center':'TensorStep([[200]])'}>
```

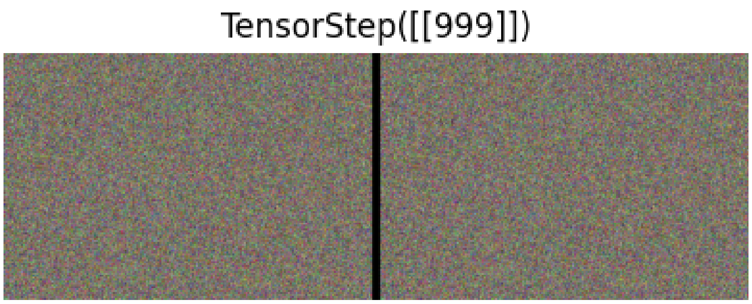


Lets now test so make sure our noise is being generated correctly.

```
noise_tuple=LabelToNoise.encodes(DiffusionTuple(img[0].detach().clone(),TensorStep(torch.t
```

```
norm.decode(diff_trans(noise_tuple)).show(show_noise=True)
```

```
<AxesSubplot:title={'center':'TensorStep([[999]])'}>
```



These are not exactly the same as it is one noising step, but they are fairly close.

```
is_close(norm.decode(diff_trans(noise_tuple))[0],TensorImage(norm.decode(diff_trans(noise_
```

```
TensorImage(True, device='cuda:0')
```

Going from noise to and image, p_sampling

```
@patch
def __call__(self:DDPM_P_Sampling,x,es,ns_t,t=None):
    t= self.t_sched[ns_t] if(t is None) else t[...,None,None,None]
    n=torch.randn_like(x)
    e,a,b=self._noise_at_t(es,t),self.ns.alphas[t],self.ns.betas[t]
    signal = (x - e) / (a ** 0.5)
    noise = b**.5 * n
    return signal + noise
@patch
def _noise_at_t(self:DDPM_P_Sampling,es,t):
    eps_coef = (1 - self.ns.alphas[t]) / (1 - self.ns.alpha_bar[t]) ** .5
    return eps_coef* es
```

We implement DDIM sampling here, as it drastically reduces sampling time from 1000 steps to 50. Just generally helps us keep our sanity when trying to show our results.

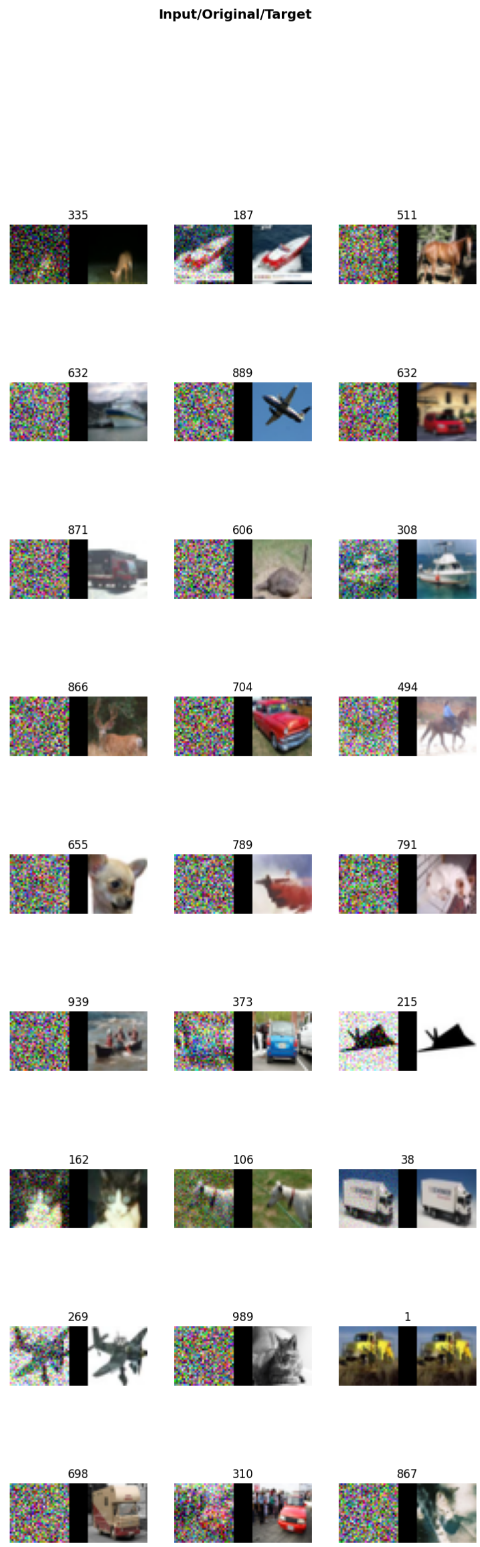
```
@patch
def __call__(self:DDIM_P_Sampling,z,es,ns_t,t=None):
    if(t is None): t=self.t_sched[ns_t]
    tp1=self.t_sched[ns_t-1]
    a,a_tp1=self.ns.alpha_bar[t][...,None,None,None],self.ns.alpha_bar[tp1][...,None,None,
    if self.predicts_x:
        xs=es
        es=(z - (a)**.5 * xs)/(1-a)**.5
    else: xs=(z - (1-a)**.5 * es)/ (a ** .5)
    signal = a_tp1**.5*(xs)
    noise = (1-a_tp1)**.5*es
    return signal + noise
```

Training a model

```
path = untar_data(URLs.CIFAR)
```

```
m=Unet(dim=192+192//8,channels=3,).cuda()
```

```
bs=128
n_steps=1000
diffusion_transform = DiffusionSamplingTransform(DDPM_Q_Sampling(),Diffusion_P_Sampler(m,D
dls=DataBlock((ImageBlock(),
               ImageBlock(),
               TransformBlock(type_tfms=[DisplayedTransform(enc=lambda o: TensorStep(o))])
               ImageBlock()),
          n_inp=3,
          item_tfms=[Resize(32)],
          batch_tfms=(Normalize.from_stats(*cifar_stats),ToDiffusionTuple,LabelToNoise,dif
          get_items=get_image_files,
          get_x=[lambda x:x,lambda x:x,
                 lambda x: torch.randint(1, n_steps, (1,), dtype=torch.long)],
          splitter=IndexSplitter(range(bs)),
).dataloaders(path,bs=bs,val_bs=2*bs)
dls.show_batch()
```


Input/Original/Target
335
187
511
632
889
632
871
606
308
866
704
494
655
789
791
939
373
215
162
106
38
269
989
1
698
310
867

```python
def mse_loss_weighted(ys,targ):
    return torch.mean(targ.w_sched[...,None] * ((ys - targ).flatten(start_dim=1) ** 2))
```

```python
def snr(at): return at/(1-at)
```

```python
def continuous_weights(at):
    weights = -snr(at[1:])/(snr(at[1:])-snr(at[:-1]))
    return torch.cat((weights[0:1],weights))
```

```python
class WeightedLinSched(Callback):
    def after_pred(self):
        if(not hasattr(self,'ws')):
            self.ws = continuous_weights(LinearNoiseSchedule().alpha_bar).clip(min=1)
            self.ws /= self.ws.mean()
        ts=self.learn.xb[1].flatten()
        self.learn.yb[0].w_sched=self.ws[ts]
```

```python
learn = Learner(dls,m,mse_loss_weighted,opt_func=Adam,cbs=[FlattenCallback,WeightedLinSche
learn = learn.to_fp16()
learn.fit_flat_cos(10,lr=2e-4,wd=0.)
```

```
<IPython.core.display.HTML object>
```

epoch	train_loss	valid_loss	time
0	0.049789	0.042322	04:39
1	0.044212	0.039284	04:39
2	0.041315	0.045253	04:40
3	0.040457	0.038427	04:39
4	0.039394	0.035517	04:40
5	0.039198	0.039416	04:39
6	0.039298	0.037537	04:39
7	0.038256	0.040432	04:39
8	0.038232	0.025152	04:40
9	nan	0.036510	04:38

next check show_results

```
learn.show_results()
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```