llama2.c for Dummies

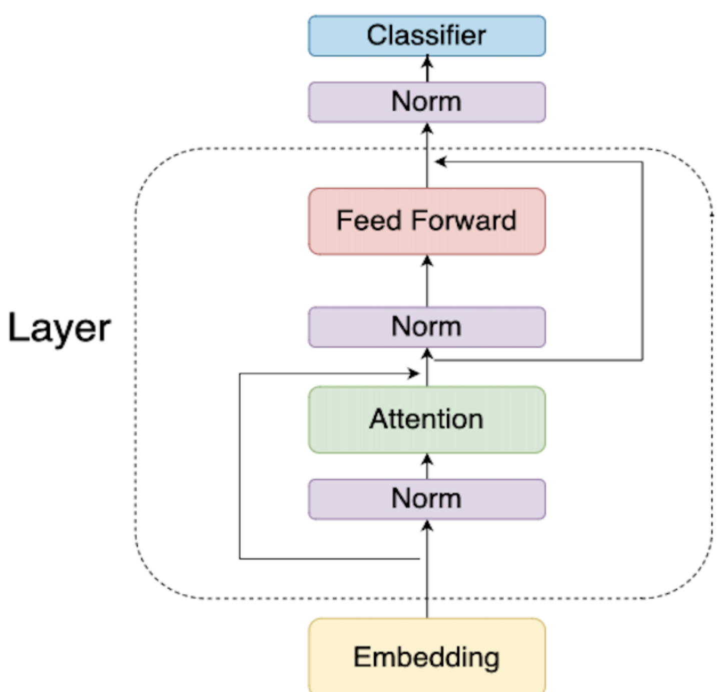
Purpose

This repo is line by line walk through of the inference file in llama2.c. Its very verbose & intended for beginners.

You will need some familiarity with transformers architecture. If you are a complete novice refer to this excellent blog first.

Prerequisites

1. Transformer architecture: 3 components
   i. Embedding (1 matmul)
   ii. Layers: matmul with Q, K , V, O and feed forward weights: W1, W2 & W3. (7 matmul)
   iii. Classifier: In our case the classifier is just matmul of `(vocab,768) x (768,1)` . Basically giving us what is the probability of each next token. (1 matmul)



Code walkthrough

Code has 3 parts, structs, functions & read logic in `main()` we will take a look at structs first, then go to main() and then cover the important functions.

PS: The code was taken from commit 4e23ad83. The original repo might be different as it gets newer commits. But 99% of the logic should remain the same :)

Part 1: Structs

We define 3 structs for storing model config, model weights & to store intermediate values (run state) during forward pass

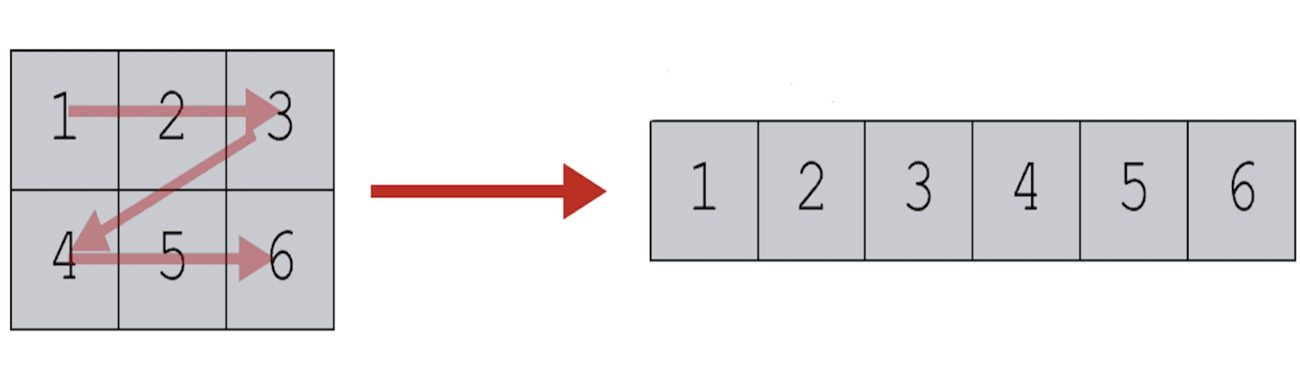
1. **Config struct**: Defines the transformer model.
   i. `n_layers` , `vocab_size` : no. of layers (e.g. llama-2 has 32 layers/BERT-base has 12 layers) & no. of tokens in our vocabulary (this is usually 30k for english languages)
   ii. `dim` and `hidden_dim` : Define shape of Q, K, V & O `(dim,dim)` and W1, W2 `(dim, hidden_dim)` & W3 `(hidden_dim, dim)`
   iii. `n_heads` : Number of heads for query(Q). If `n_heads=12` then matrix `Q=(768,768)` behaves/viewed as `(768, 768/12,768)`
   iv. `n_kv_heads` : Number of heads for K & V. **Why are these different from above?** : Read multi query paper
   v. `seq_len` : No. of tokens we will generate

```
typedef struct {
    int dim; // transformer dimension
    int hidden_dim; // for ffn layers
    int n_layers; // number of layers
    int n_heads; // number of query heads
    int n_kv_heads; // number of key/value heads (can be < query heads because of multiquery)
    int vocab_size; // vocabulary size, usually 256 (byte-level)
    int seq_len; // max sequence length
} Config;
```

2. **Weight struct** for llama. This is our pytorch `ffn=nn.Linear(...)` counterpart.
   i. Why are they `float*` ? Because all matrices are just 1d flattened array. See below diagram
   ii. code is self explanatory with shapes commented. `rms_` are weights used for normalization & `freq_cis_` are for RoPE embedding. We will look at `RoPE` in detail ahead.
   iii. `wcls` is the final classifier. Matrix of size `(vocab, dim)` that maps final embedding from a vector to probability for each token in vocab.

```
typedef struct {
    // token embedding table
    float* token_embedding_table;    // (vocab_size, dim)
    // weights for rmsnorms
    float* rms_att_weight; // (layer, dim) rmsnorm weights
    float* rms_ffn_weight; // (layer, dim)
    // weights for matmuls
    float* wq; // (layer, dim, dim)
    float* wk; // (layer, dim, dim)
    float* wv; // (layer, dim, dim)
    float* wo; // (layer, dim, dim)
    // weights for ffn
    float* w1; // (layer, hidden_dim, dim)
    float* w2; // (layer, dim, hidden_dim)
```

```
    float* w3; // (layer, hidden_dim, dim)
    // final rmsnorm
    float* rms_final_weight; // (dim,)
    // freq_cis for RoPE relatively positional embeddings
    float* freq_cis_real; // (seq_len, dim/2)
    float* freq_cis_imag; // (seq_len, dim/2)
    // (optional) classifier weights for the logits, on the last layer
    float* wcls;
} TransformerWeights;
```



3. Intermediate activations (Run state)
   i. During forward pass we need to store intermediate values, e.g. output of matmul or output after norm. Will take a look at all variables later
   ii. `key_cahce` and `value_cache` store the key, value outputs of previous tokens. e.g. during inference if the 5th token is being generated, this will store `key` , `value` of the previous 4.

```
typedef struct {
    // current wave of activations
    float *x; // activation at current time stamp (dim,)
    float *xb; // same, but inside a residual branch (dim,)
    float *xb2; // an additional buffer just for convenience (dim,)
    float *hb; // buffer for hidden dimension in the ffn (hidden_dim,)
    float *hb2; // buffer for hidden dimension in the ffn (hidden_dim,)
    float *q; // query (dim,)
    float *k; // key (dim,)
    float *v; // value (dim,)
    float *att; // buffer for scores/attention values (n_heads, seq_len)
    float *logits; // output logits
    // kv cache
    float* key_cache;   // (layer, seq_len, dim)
    float* value_cache; // (layer, seq_len, dim)
} RunState;
```

We will take a look at functions as we encounter them. For now lets see the logic inside `main()`

Part 2: Main (Can skip this part if you are only interested in forward logic)

1. Get command line arguments. Nothing interesting. Currently you can call `run.c` with
   i. `./run llama2_7b.bin`
   ii. `./run llama2_7b.bin 0.1` -> with temperature
   iii. `./run llama2_7b.bin 0.1 100` -> with temperature & steps (no. of output tokens generated)
2. Declare `config` & `weights` in the end

```
int main(int argc, char *argv[]) {
    // poor man's C argparse
    char *checkpoint = NULL;  // e.g. out/model.bin
    float temperature = 0.9f; // e.g. 1.0, or 0.0
    int steps = 256;          // max number of steps to run for, 0: use seq_len
    // 'checkpoint' is necessary arg
    if (argc < 2) {
        printf("Usage: %s <checkpoint_file> [temperature] [steps]\n", argv[0]);
        return 1;
    }
    if (argc >= 2) {
        checkpoint = argv[1];
    }
    if (argc >= 3) {
        // optional temperature. 0.0 = (deterministic) argmax sampling. 1.0 = baseline
        temperature = atof(argv[2]);
    }
    if (argc >= 4) {
        steps = atoi(argv[3]);
    }
        // seed rng with time. if you want deterministic behavior use temperature 0.0
    srand((unsigned int)time(NULL));
    // read in the model.bin file
    Config config;
    TransformerWeights weights;
```

2. Reading `checkpoint` file.
   i. If you are familiar with PyTorch. Usually `config.json` & `model.bin` are separate (we load weights like a dictionary). But here `train.py` saves everything in one `.bin` file in a specific format. This specific format allows us to easily read config & then each weight one by one.

   Details

   i. `shared_weights` : Should input embedding matrix & output classifier matrix be same?
   ii. Next load into `weights` . Get file size via `file_size = ftell(file);` Unlike vanilla PyTorch inference we **don't** load all weights into RAM. Instead we call `mmap(..)` to allocate RAM memory when we want lazily. For more detail read
   iii. Finally call `checkpoint_init_weights` (snippet of function below). Here we map our weight pointers to correct address returned by `mmap` . Since we already read config we offset for it in line `float* weights_ptr = data + sizeof(Config)/sizeof(float);`

```
void checkpoint_init_weights(TransformerWeights *w, Config* p, float* f, int shared_weights){
float* ptr = f;
w->token_embedding_table = ptr;
ptr += p->vocab_size * p->dim;
w->rms_att_weight = ptr;
.......
}
```

Original code we are talking about in above section

```
    int fd = 0;
    float* data = NULL;
    long file_size;
    {
        FILE *file = fopen(checkpoint, "rb");
        if (!file) {
            printf("Unable to open the checkpoint file %s!\n", checkpoint);
            return 1;
        }
            // read in the config header
        if(fread(&config, sizeof(Config), 1, file) != 1) { return 1; }
        // negative vocab size is hacky way of signaling unshared weights. bit yikes.
        int shared_weights = config.vocab_size > 0 ? 1 : 0;
        config.vocab_size = abs(config.vocab_size);
        // figure out the file size
        fseek(file, 0, SEEK_END); // move file pointer to end of file
        file_size = ftell(file); // get the file size, in bytes
        fclose(file);

        // memory map the Transformer weights into the data pointer
        fd = open(checkpoint, O_RDONLY); // open in read only mode
        if (fd == -1) { printf("open failed!\n"); return 1; }
        data = mmap(NULL, file_size, PROT_READ, MAP_PRIVATE, fd, 0);
        if (data == MAP_FAILED) { printf("mmap failed!\n"); return 1; }
        float* weights_ptr = data + sizeof(Config)/sizeof(float);
        checkpoint_init_weights(&weights, &config, weights_ptr, shared_weights);
    }
```

3. Reading vocab file -> Mostly straightforward, only few details
    i. `vocab` is `char**` since each token is a string & `vocab` is a list of tokens.
    ii. For loop over `vocab_size` & read each token

```
// right now we cannot run for more than config.seq_len steps
    if (steps <= 0 || steps > config.seq_len) { steps = config.seq_len; }
    // read in the tokenizer.bin file
    char** vocab = (char**)malloc(config.vocab_size * sizeof(char*));
    {
```

```
    FILE *file = fopen("tokenizer.bin", "rb");
    if (!file) {
        printf("Unable to open the tokenizer file tokenizer.bin! Run "
        "python tokenizer.py to convert tokenizer.model -> tokenizer.bin\n");
        return 1;
    }
    int len;
    for (int i = 0; i < config.vocab_size; i++) {
        if(fread(&len, sizeof(int), 1, file) != 1) { return 1; }
        vocab[i] = (char *)malloc(len + 1);
        if(fread(vocab[i], len, 1, file) != 1) { return 1; }
        vocab[i][len] = '\0'; // add the string terminating token
    }
    fclose(file);
}
```

Forward Loop & sampling in main (Go to important part)

1. Allocate memory for run state/intermediate values. The first `token` we pass into our model is BOS token ("Beginning of Statement") who's vocab index is `1`.

```
RunState state;
malloc_run_state(&state, &config);

// the current position we are in
long start = time_in_ms();
int next;
int token = 1; // 1 = BOS token in Llama-2 sentencepiece
int pos = 0;
printf("<s>\n"); // explicit print the initial BOS token (=1), stylistically symmetric
```

2. Forward loop:

   i. `transformer(token, pos, &config, &state, &weights);` stores classifier score of each token as being the next token in sequence inside `state.logits` .(contents of `transformer` function convered in next section).

   ii. Next we sample. **Why we need sampling & how to do it?**

      - Lets say you want AI to complete dialogues of a movie & your input is *"Luke, I am your"* . Now `llama` gives you score for each token to be the next word. So e.g. assume our tokens are `["Apple", "Football", "Father", "Brother"]` & llama gives them scores of `[0.3, 0.1, 0.9, 0.7]` . Now to pick the next token, either we take maximum (`"Father"` with score 0.9) or we sample tokens with a probability proportional to thier score, this way we can get more diversity(very important in today's world 😁) in our prediction.

   iii. Lets discuss some more details: If `temperature=0` then its max sampling. For `temperate>0` we convert `state.logits` into probabilities using softmax & store back in `state.logits` . The `sample(..)` function returns a token sampled from the `state.logits` probability distribution. Read more here

   iv. The token generated `next` becomes the next input token in line `token=next` .

```
while (pos < steps) {
        // forward the transformer to get logits for the next token
        transformer(token, pos, &config, &state, &weights);
        // sample the next token
```

```
        if(temperature == 0.0f) {
            // greedy argmax sampling
            next = argmax(state.logits, config.vocab_size);
        } else {
            // apply the temperature to the logits
            for (int q=0; q<config.vocab_size; q++) { state.logits[q] /= temperature; }
            // apply softmax to the logits to get the probabilities for next token
            softmax(state.logits, config.vocab_size);
            // we now want to sample from this distribution to get the next token
            next = sample(state.logits, config.vocab_size);
        }
        printf("%s", vocab[next]);
        fflush(stdout);

        // advance forward
        token = next;
        pos++;
    }
```

Actual Forward pass

Details of `transformer(token, pos, &config, &state, &weights);` called from `main()`

Section below uses 2d/3d array indexing extensively. We cover it briefly here to make life easier

1. If matrix `float* mat` is of size `(dim1, dim2, dim3)` then pointer to access `mat[l][i][j]` is `dim2*dim3*l + dim3*i + j;` - This is `formula-1` we will refer to this often later. Read link if you are confused

How to view matrices in terms of head?

1. K (key) `float* wk` is a matrix defined as shape `(layer, dim, dim)` when viewed in terms of heads is `(layer, dim, n_heads, head_dim)`

1. Convenience variables. Nothing interesting apart from copying the embedding of `token` into `s->xb` using `memcpy`. Why not use `float* content_row` itself? Because `s->xb` is going to change & using `content_row` will change model weights.

```
void transformer(int token, int pos, Config* p, RunState* s, TransformerWeights* w) {
    // a few convenience variables
    float *x = s->x;
    int dim = p->dim;
    int hidden_dim =  p->hidden_dim;
    int head_size = dim / p->n_heads;
    float* content_row = &(w->token_embedding_table[token * dim]);
    // copy the token embedding into x
    memcpy(x, content_row, dim*sizeof(*x));
```

RoPE : Rotary Positional Embeddings

- Formulation: Transforms feature pairs by rotating it in 2D plane. e.g. If your vector is `[0.8, 0.5, -0.1, 0.3]` we group them into pairs: `[[0.8,-0.1], [0.5, 0.3]` and rotate by some angle . This is ~~part of the weights & is learned during training~~ is fixed from the start (its not learnable). In the paper the value of is

RoPE Formula (For 2 features grouped into a pair) is below. is the index of the pair. is a learned parameter that we load from `.bin` file

Our example pair `[[0.8,-0.1], [0.5, 0.3]` will be transformed like below. Keep in mind for the first pair `[0.8, 0.1]` since (therefore). And for 2nd pair `m=1`

Combining both, the output is `[[0.8, 0.1], [0.58, 0.08]]` now **un-pairing** them will give us `[0.8, 0.58, 0.1, 0.08]` So `RoPE` transformed `[0.8, 0.5, -0.1, 0.3]` into `[0.8, 0.58, -0.1, 0.08]` . Keep in mind if a feature is of `dim=768` then there are half of it **384** 's.

Back to code

1. We get for current position (`pos` is our). `freq_cis_real_row` is and `freq_cis_imag_row` is .

```
// pluck out the "pos" row of freq_cis_real and freq_cis_imag66
float* freq_cis_real_row = w->freq_cis_real + pos * head_size / 2;
float* freq_cis_imag_row = w->freq_cis_imag + pos * head_size / 2;
```

2. Iterate over layers. Apply `rmsnorm` to input of the layer. `rmsnorm` function calculates the below

.

where is input, is learnable parameter (`w->rms_attn_weight` below) & is `dim` .

`matmul` does matrix mult of a 2d matrix with a 1d matrix. `(A, B) x (A,)` . The implementation is trivial (we cover this at very end). We multiply Q,K,V with `s->xb` (output of `rmsnorm`) and store output in `s->q` , `s->k` ..

```
for(int l = 0; l < p->n_layers; l++) {
// attention rmsnorm
        rmsnorm(s->xb, x, w->rms_att_weight + l*dim, dim);

        // qkv matmuls for this position
        matmul(s->q, s->xb, w->wq + l*dim*dim, dim, dim);
        matmul(s->k, s->xb, w->wk + l*dim*dim, dim, dim);
        matmul(s->v, s->xb, w->wv + l*dim*dim, dim, dim);
```

3. Go over each head & apply the 2-d /sin transformation we discussed above to `s->q` and `s->k`. We do it separately for each head, therefore we take offset of `h*head_size`

```
// apply RoPE rotation to the q and k vectors for each head
        for (int h = 0; h < p->n_heads; h++) {
            // get the q and k vectors for this head
            float* q = s->q + h * head_size;
            float* k = s->k + h * head_size;
            // rotate q and k by the freq_cis_real and freq_cis_imag
            for (int i = 0; i < head_size; i+=2) {
                float q0 = q[i];
                float q1 = q[i+1];
                float k0 = k[i];
                float k1 = k[i+1];
                float fcr = freq_cis_real_row[i/2];
                float fci = freq_cis_imag_row[i/2];
                q[i]   = q0 * fcr - q1 * fci;
                q[i+1] = q0 * fci + q1 * fcr;
                k[i]   = k0 * fcr - k1 * fci;
                k[i+1] = k0 * fci + k1 * fcr;
            }
        }
```

4. Once we get `q, k, v` for current token, we need to calculate self-attention. Where we multiply query into key. `k & v` are only for the current token. We store the `k, v` for all past tokens in `key_cache_row` & `value_cache_row`.
    - For example, if we have generated the tokens ("fox", "jumps", "over") until now then we already have Q & V for "fox" & "jumps" from previous forward passes stored in our cache. We need not recalculate.
    - Since caches store key, query for all layers & for all tokens (max no.of tokens is `seq_length`) its dimensions are `(layer, seq_length, dim)`. `seq_length` is usually called `context`.
5. Consider below code in terms of above example. Lets say `seq_length=32` (which means we generate at-most 32 tokens). `pos=2` since "fox" is the 3rd token (2nd since python is 0-indexed).
    - We already have `layer*(pos-1)*dim` values filled in `s->key_cache` We need to fill the key, value of current token "fox" into `s->key_cache` too before doing self-attention. This is what `memcpy(key_cache_row, s->k, dim*sizeof(*key_cache_row));` does

```
// save key,value at this time step (pos) to our kv cache
int loff = l * p->seq_len * dim; // kv cache layer offset for convenience
float* key_cache_row = s->key_cache + loff + pos * dim;
float* value_cache_row = s->value_cache + loff + pos * dim;
memcpy(key_cache_row, s->k, dim*sizeof(*key_cache_row));
memcpy(value_cache_row, s->v, dim*sizeof(*value_cache_row));
```

Doing self-attention

Formula

In above is `pos` (current length of the generated text)

This part of the code becomes easy if you remember that `s->q`, `s->k` when viewed in terms of heads are of shape `(dim, n_heads, head_dim)` & `key_cache`'s are `(seq_length, n_heads, head_dim)`. Lets go over the code

1. `int h` is the current head count. Lets look at each line one by one
   i. `q = s->q + h*head_size` : Gets pointer to start of head. Remember `formula-1`. Matrix is of size `(dim, n_heads, head_dim)` we need `s->q[0][h][0]` which is `0*n_heads*head_dim + h*head_dim + 0` which is `h*head_size`.
   ii. `att = s->att + h * p->seq_len` : We will store attention in `s->attn` run state variable.
   iii. For each position (`pos` is 2 currently if you go back to "fox", "jumps", "over" example) 1.To get layer, position & head we do `s->key_cache + l*seq_length*dim + t*n_heads*head_dim + h*head_dim`. Since `loff` defined before is already `l*seq_length*dim`. Final offset is `loff + t*n_heads*head_dim + h*head_size` since `n_heads*head_dim=dim` we get offset as `loff + t*dim + h*head_size`.
   iv. We now have `q` `(head_size,)`, `k` `(head_size,)` & `att` `(seq_length,)`. We can calculate self-attention score for head at position . We sum this over all the heads & positions till now.

```
int h;
#pragma omp parallel for private(h)
for (h = 0; h < p->n_heads; h++) {
// get the query vector for this head
float* q = s->q + h * head_size;
// attention scores for this head
float* att = s->att + h * p->seq_len;
// iterate over all timesteps, including the current one
for (int t = 0; t <= pos; t++) {
        // get the key vector for this head and at this timestep
        float* k = s->key_cache + loff + t * dim + h * head_size;
        // calculate the attention score as the dot product of q and k
        float score = 0.0f;
        for (int i = 0; i < head_size; i++) {
                score += q[i] * k[i];
        }
        score /= sqrtf(head_size);
        // save the score to the attention buffer
        att[t] = score;
```

2. `attn` obtained above is of shape `(seq_length, )`. Next we multiply it with `v` which is `(seq_length, dim)`. Remember the below loop is inside the `for (h = 0; h < p->n_heads; h++)` that started in previous section.

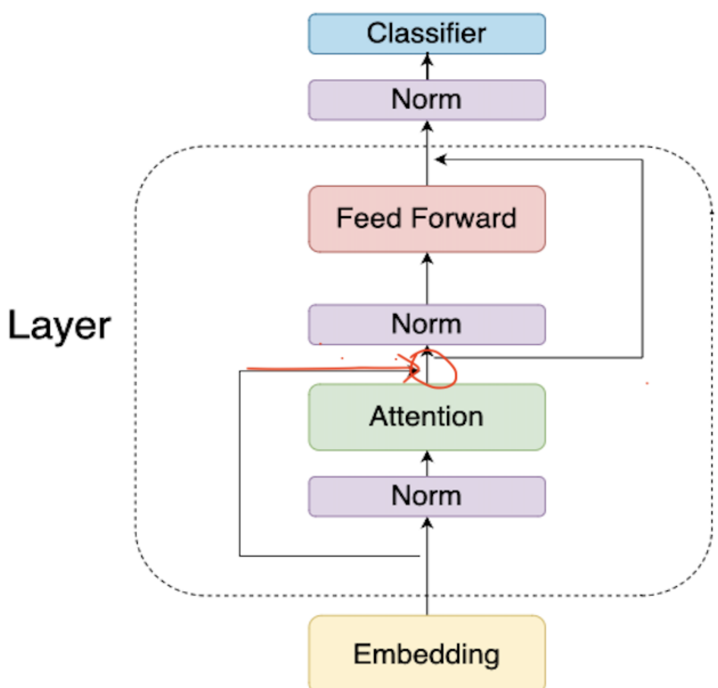
```
// softmax the scores to get attention weights, from 0..pos inclusively
softmax(att, pos + 1);

// weighted sum of the values, store back into xb
```

```
float* xb = s->xb + h * head_size;
memset(xb, 0, head_size * sizeof(float));
for (int t = 0; t <= pos; t++) {
        // get the value vector for this head and at this timestep
        float* v = s->value_cache + loff + t * dim + h * head_size;
        // get the attention weight for this timestep
        float a = att[t];
        // accumulate the weighted value into xb
        for (int i = 0; i < head_size; i++) {
                xb[i] += a * v[i];
        }
}
```

Feed Forward & Classifier

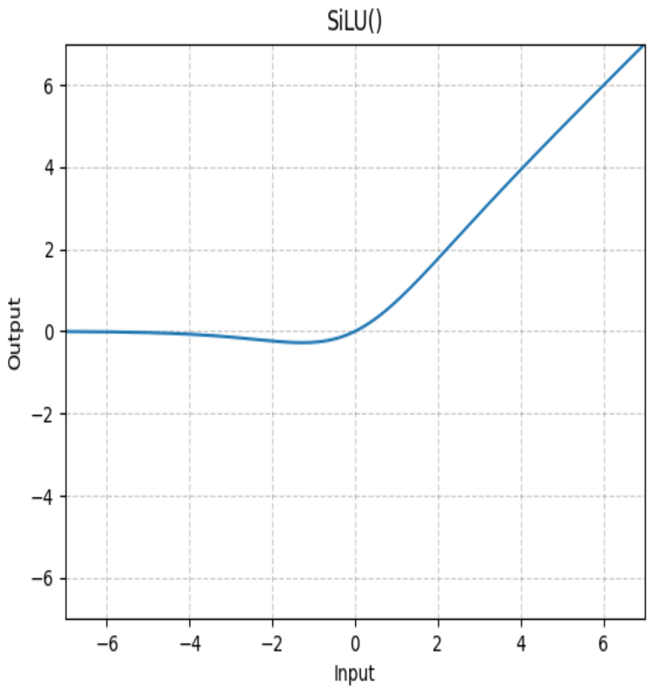
1. To complete attention module, we need to multiply with which we do in first line. Next line `accum` adds input which comes from skip layer (red arrow) & output of attention. Followed by normalization.

```
// final matmul to get the output of the attention
matmul(s->xb2, s->xb, w->wo + l*dim*dim, dim, dim);
// residual connection back into x
accum(x, s->xb2, dim);
// ffn rmsnorm
rmsnorm(s->xb, x, w->rms_ffn_weight + l*dim, dim);
```



2. Next we calculate the FFN output which is

is `silu` activation.



This portion is self explanatory

```
// Now for FFN in PyTorch we have: self.w2(F.silu(self.w1(x)) * self.w3(x))
// first calculate self.w1(x) and self.w3(x)
matmul(s->hb, s->xb, w->w1 + l*dim*hidden_dim, dim, hidden_dim);
matmul(s->hb2, s->xb, w->w3 + l*dim*hidden_dim, dim, hidden_dim);
// F.silu; silu(x)=x*σ(x),where σ(x) is the logistic sigmoid
for (int i = 0; i < hidden_dim; i++) {
        s->hb[i] = s->hb[i] * (1.0f / (1.0f + expf(-s->hb[i])));
}
// elementwise multiply with w3(x)
for (int i = 0; i < hidden_dim; i++) {
        s->hb[i] = s->hb[i] * s->hb2[i];
}
// final matmul to get the output of the ffn
//memcpy(tmp_w_hid, w->w2 + l*dim*hidden_dim, hidden_dim*dim*sizeof(float));
matmul(s->xb, s->hb, w->w2 + l*dim*hidden_dim, hidden_dim, dim);
```

3. The last line is another accum (2nd skip layer in above diagram)

```
accum(x, s->xb, dim);
```

Final Classifier

After running above module for all layers, we get an embedding of shape `(dim,)`. We need to convert this into a vector of shape `(vocab,)` whose each entry tells us what is the score for that word to be next token.

1. Before multiplying with classifier matrix (`w->wcls`) we normalize our embedding. The scores our saved in `s->logits`

```
// final rmsnorm
rmsnorm(x, x, w->rms_final_weight, dim);
// classifier into logits
matmul(s->logits, x, w->wcls, p->dim, p->vocab_size);
```

The end

Once we get `s->logits` we sample next token (do this until we get `seq_length` tokens). This has already been covered in "Forward Loop & sampling in main" section. Congratulations! now you know how LLMs work & how to code them in C. If you now want to know how to code them in Python know, refer to modelling_llama.py

Here is a picture of a cat :)